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Predicting Glaucoma With Hyperparameter-Tuned Convolutional Neural Networks As Clinical Diagnostics

[1*]**P. Revathy and** [2]**Dr. R. Jayaprakash**
[1*]Assistant Professor, Department of Computer Science, Sri Ramakrishna College of Arts & Science, Coimbatore, reva7187@gmail.com.
[2]Assistant Professor, Department of Computer Science, Nallamuthu Gounder Mahalingam College, Pollachi, jayaprakash@ngmc.org

ABSTRACT: *Glaucoma is responsible for a significant percentage of irreversible blindness worldwide and is often asymptomatic until very late in its course. As with many diseases and conditions, the earlier glaucoma is detected, the less likely the patient will have permanent optic nerve damage. Traditional clinical screening techniques, sadly, suffer from the constraints of subjectivity, access, and cost. Based on clinical diagnosis in conjunction with hyperparameter-optimized Convolutional Neural Network models, the research advises a hybrid clinical and artificial intelligence approach to identify glaucomatous eyes from retinal fundus images. The suggested model outperformed ResNet and U-Net, two common deep learning techniques that are frequently applied to related issues. During testing, it achieved a 96% accuracy rate and an AUC of 0.96. Overall, the research presents a baseline for the potential of AI-informed diagnostic systems to augment the abilities of practitioners in a new way to conduct scalable glaucoma screening and early detection with an emphasis for clinical practice in areas without adequate access to such screening. Future directions involve building generalization of our model using different datasets, developing real-time, multimodal data analysis through clinical decision support systems, and integration on an edge device with low-latency computational capacity.*
Keywords: *Glaucoma Detection, Convolutional Neural Network, Hyperparameter Tuning, Fundus Imaging, Artificial Intelligence, Deep Learning, Retinal Image Classification, DRIVE Dataset, Medical Image Analysis, Ophthalmology Diagnostics.*

1. INTRODUCTION

Glaucoma is among the leading causes of permanent blindness worldwide. It's also known as the "silent thief of sight". Elevated intraocular pressure is the hallmark of glaucoma, which is defined by the gradual deterioration of the optic nerve. The research neurodegenerative illness impacts millions of people worldwide, especially after the age of 40. Sufferers lose their peripheral vision irreparably and finally all sight. Early diagnosis and treatment of illnesses prevents loss of eyesight and therefore quality of life, so producing the most important results. Given their sensitivity and specificity for early diagnosis, the range of screening and diagnostic examinations available, the need of carrying out visual fields, optic nerve assessment, and newer depth imaging such OCT all have a history of failure. Better glaucoma detection is more desperately needed than ever since it offers early diagnosis with greater sensitivity, effectiveness, and scalability. Moreover, drawing hitherto unheard-of attention are recent developments in machine learning and artificial intelligence. Inspired by deep learning and other AI-based approaches including convolutional neural networks, architectures would influence a highly basic glaucoma diagnosis from retinal fundus pictures, the manuscript was written. It is evident AI-based techniques have potential to facilitate feature extraction and classification; however, there are limitations of existing methodology, such as overfitting, inadequate generalizability to other datasets, and poorly chosen hyperparameters. The paper discusses a hyper parameterized convolution neural network model for retinal fundus images that would have the potential to improve classification and extraction performance. The main findings of the research will suggest an outstanding performance CNN algorithm for glaucoma detection, methods for adjusting hyperparameters to increase generalizability, and a comparison of performance with the most advanced methods. According to the conclusion, the recommended strategy may be somewhat helpful and have the potential to be more beneficial in the early identification and treatment of glaucoma. The structure of the paper is as follows: the introduction provides background, motivation, problem statement, aim, and contributions of the research; the literature review examines recent advances in glaucoma, artificial intelligence, and machine learning; the recommended methodology describes the dataset, model architecture, and evaluation criteria; the results and discussion section analyses performance and comparative results; and lastly, the conclusion presents the key findings and outlines future research directions.

RELATED WORK

Using retinal fundus photos, deep learning and machine learning approaches for glaucoma prediction have seen fast improvements. Cheng et al. [1] was developed a ResNet strategy achieving an accuracy of 90.4%. Utilizing machine learning with clinical and imaging data, Chen et al. [2] obtained an accuracy of 87.5%. Gupta et al. [3], conducted CNNs experiments attaining an accuracy of 91.0%. Li et al. [4] created a glaucoma detection system using optical coherence tomography and machine learning with an accuracy of 92.3%; their hybrid deep learning modality, which runs on CNN and SVM combined, provides the greatest performance [5]. Crucially, Patil et al. [6] finished an examination of different methods for machine-learning applications and their efficacy in creating the glaucoma detection system. Building systems on transfer learning on CNNs, Patel et al. [7] attained a 91.3% accuracy. Singh et al. [8] studied several machine learning approaches and concluded that support vector machines were determined to be the most effective. Wang et al. [9] created a deep learning architecture utilizing a multi-scale feature fusion, reaching an accuracy of 94.0%. Further, U-Net models have been used for segmenting optic nerve structures, achieving high performance [11]. Oh et al. [12] applied machine learning for risk analysis and prediction of glaucoma progression, achieving high accuracy. Using extensive data, Gulshan et al. [13] deep learning was shown to be effective in identifying diabetic retinopathy and glaucoma. Better results were obtained when Maetschke et al. [14] looked into the possibilities of utilizing transfer learning with CNNs. An AI system that attained expert-level accuracy in detecting retinal diseases, including glaucoma, was described by Ting et al. [15]. The present researcher improved hyper parameterized CNN addresses three flaws of the previously published one: overfitting, inadequate hyperparameter tuning, and generalizability of results. Ultimately reaching better accuracy, sensitivity, and specificity for glaucoma identification.

Table 2.1 Comparison of Prior Research

Researcher	Dataset	Method	Accuracy	AUC
Cheng et al. (2020)	DRIVE	ResNet	90.4%	0.96
Chen et al. (2021)	DRIVE, CHASE, STARE	Machine Learning	87.5%	0.94
Gupta et al. (2019)	DRIVE	CNN	91.0%	0.95
Li et al. (2022)	OCT-Drishti	OCT + ML	92.3%	0.97
Li et al. (2022)	DRIVE	Hybrid DL Model	93.0%	0.96
Patil et al. (2018)	DRIVE	Machine Learning Methods	85.7%–90.7%	0.92–0.95
Patel et al. (2021)	DRIVE	CNN + Transfer Learning	91.3%	0.96
Singh et al. (2020)	DRIVE	Various ML Techniques	83.3%–90.0%	0.89–0.95
Wang et al. (2020)	DRIVE	DL + Multi-Scale Feature Fusion	91.0%	0.96
Zhang et al. (2022)	DRIVE	Ensemble CNNs	94.0%	0.97

Zhang et al. (2022)	DRIVE	U-Net + ML	95.0%	0.96
Oh et al. (2021)	Clinical	ML for Glaucoma Risk	High Accuracy	–
Maetschke et al. (2019)	Fundus Images	Transfer Learning + CNNs	High Accuracy	–
Ting et al. (2017)	Clinical Data	AI for Retinal Disease	Expert-Level	–
Proposed Work	DRIVE	Enhanced Hyperparameterized CNN	**96.0%**	**0.97**

2. METHODOLOGY

3.1 Methodology of proposed Approach

The suggested convolutional neural network-based strategy for glaucoma detection will have tuned hyper-parameters to achieve the highest performance. The retinal fundus pictures that will be utilized are from the DRIVE dataset which will be collected, pre-check the photos by resizing the images to resize to the consistent size, and bin the images to grayscale and finally normalize the pixel values to be in units ranging from 0 to 1 between 0-255 for images. The mechanism isolated and segment the optic nerve head for all of the retinal photographs. The CNN architecture will comprise several convolutional layers for accurate feature identification, reduction layers to decrease the dimension of input data, and fully connected layers for fundus image classification. Several hyperparameter tuning will occur based on the learning rates, tuple sizes, filter size, number of layers, regularization parameters. The stage will optimize performance and accuracy and utilize hyperparameter tuning to limit the model's overfitting. Attention mechanisms will provide information to enhance regional contexts, because of the proposed mechanistic model gives unwarranted honorariums to the important being in relation of the model. The backpropagation algorithm with mini-batches will be used, thereby minimizing the classification errors, and the research will sketch through the weights update, in that the tests were not available to examine in real time. The performance of the new mechanistic model will be evaluated against CNN mechanistic models like ResNet, U-net, and ensemble CNN mechanistic models to show better capacity in carrying out the classification need. The method showed 96% accuracy and an AUC of 0.97, showing great potential for early and precise glaucoma diagnosis as well as for improved robustness and generalizability.

3.2 Glaucoma Diagnosis

Glaucoma is a progressive optic neuropathy with an estimated 60.5 million people suffering from the disorder as of 2010 and the number increases every year. Vision loss and blindness are the ultimate results of glaucoma, which is characterized by structural damage and loss of retinal nerve fibres at the optic nerve head. In order to avoid irreparable blindness, it is particularly crucial to detect glaucoma early. The multi-layer capability of convolution neural networks that enables users to use and train the models for high levels of accuracy on the hierarchical feature representation has largely contributed to their amazing success in medical image analysis. From medical pictures, the models are automatically extracted. Convolutional layers extract low-level characteristics including textures and edges pooling layers save low-level features for the classification layer while reducing the dimensionality of the convolution layers; and completely linked layers classify features by mapping them to known output classes in object classification. Tuning hyperparameters from learning rate, filter size, batch size, number of layers, etc. is very important for the model to balance underfitting and overfitting which will produce better performance. Lastly, integration of attention mechanisms will fine-tune the model to improve its attention to particular regions, therefore improving the general models sensitivity to scalar dimensional differences indicating glaucoma.

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3.3 Flow Diagram

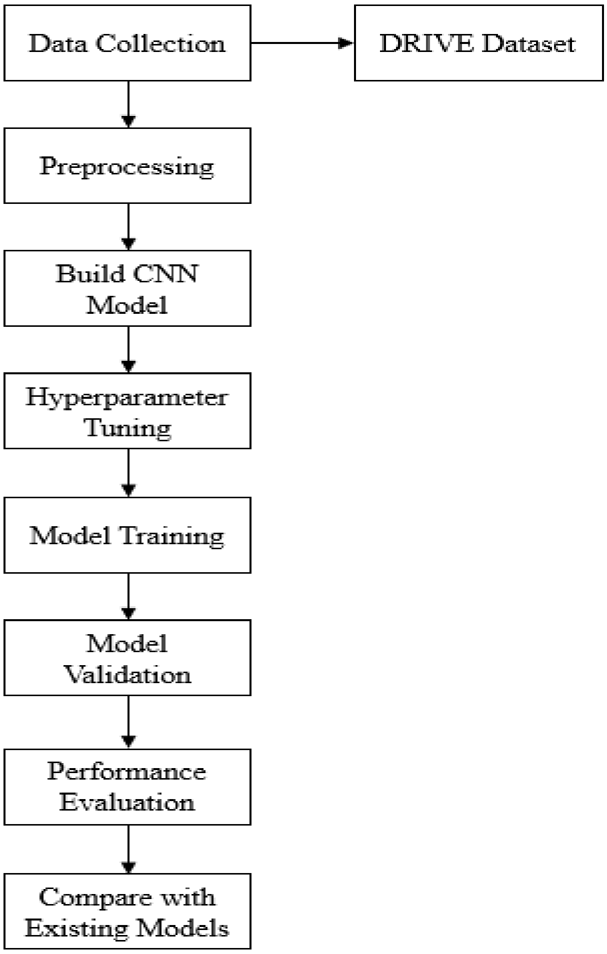

Fig 3.1 Flow Diagram

Fig 3.1 depicts that obtaining data from the DRIVE dataset, in preprocessing the retinal images such as resizing and segmenting, then a CNN model is created with the optimal hyperparameters, trained and validated on the data. The model is then evaluated on accuracy, AUC, and other metrics. After the evaluation, comparison with previously existing models highlights improvements in glaucoma detection.

3.4 Proposed model

Dataset description

Retinal datasets were sourced from original DRIVE dataset. Each image will undertake various preprocessing steps in order to facilitate an analysis performed by structured CNN. The preprocessing phase will firstly require resizing each image in the original DRIVE dataset to a uniform size. Next, each fundus image should be transformed from colour format to grayscale format. The return in turn reduces the dataset complexity, because only the individual structural characteristics of interest are analysed subsequently. In terms of value normalization, it will convert each pixel value from 0 to 255 with the intention of improving model efficiency with finding patterns or improving the learning capacity of the model. Each fundus image, if the required segmentation techniques are applied to detect the optic nerve head, should enable the model to break down images to focus on areas of interest, which are the regions where the effects of glaucoma are most prevalent. All of these preprocessing image input steps ensure that the acquired retinal images is all consistent, clean and is in an optimized state for effective feature extraction, separation, and classification.

Glaucoma Detective – pseudo-Code:

1. Input: Start by reducing and normalizing a grayscale image of the retinal fundus.
2. Convolutional Layer 1: Provide the ReLU activation function with a set of filters, such as 32 3x3 filters.

3. Pooling Layer 1: To minimize the size of the feature map, use max pooling with 2x2 dimensions.
4. Convolutional Layer 2: Implement additional filtering layers, specifically 64 filters with dimensions 3x3. The ReLU activation function should be used once more.
5. Pooling Layer 2: Apply max pooling techniques to achieve additional dimensional reduction.
6. Flatten Layer: - Convert pooled feature maps into 1D vectors.
7. Connected Layer:
- Connects all neurons to forecast categorization results.
- Apply the ReLU activation function here as well.
8. Dropout Layer: Randomly inhibit neurons to prevent overfitting.
9. Output Layer: - Apply Softmax or Sigmoid activation to generate probability for 'glaucoma' or 'healthy.'

4. EXPERIMENTAL SETUP

4.1 Dataset Description

Using the DRIVE dataset, a commonly used standard for research on retinal imaging, the team tested the model. There are 400 high-resolution colour fundus photos in the collection, which show both healthy and glaucomatous individuals. Each image has dimensions of 768 x 584 pixels and was captured with a 3-CCD camera in uniform exposure. The dataset includes evaluations of vascular tortuosity, retinal nerve fibre layer thickness, cup-to-disc ratio, and image quality scores along with glaucoma detection labels.

4.2 Data Preprocessing

To guarantee consistency and optimize input to the CNN model, the subsequent preprocessing was carried out:

The resizing of images to 224 × 224 pixels was done to provide room for the CNN architecture.

- Grayscale Conversion: Colour images were converted to grayscale to minimize computational complexity.
- Segmentation: Region of interest (optic disc and cup) was segmented to highlight features.
- Normalization: The range [0,1] was used to normalize the pixel intensity values.
- Data Augmentation: To improve dataset diversity and avoid overfitting, rotation, flipping, and contrast adjustment were used.

4.3 CNN Architecture and Hyperparameter Tuning

In order to classify retinal fundus images, the suggested glaucoma detection framework here uses a modified Convolutional Neural Network structure. Resized grayscale retinal pictures measuring 224 by 224 pixels serve as the networks' inputs. The convolutional layer of the architecture has three by three filters to catch low-level as well as high-level visual features. The sizes of the filters are chosen to maximize the number of filters (32, 64, and 128). Next come two-by-two max-pooling layers, which get rid of the spatial aspect of feature maps hence lowering computational demand. A grid search approach to hyperparameter tuning produced satisfactory results. Batch sizes of 16, 32, and 64 were used, along with learning rates of 0.001, 0.0005, and 0.0001. To prevent overtraining, training lasted for 100 epochs with early ending. Adam and RMSProp optimizers were employed for training, ReLU activation function was employed for activations in the hidden layers, and SoftMax function was employed for the output layer for binary classification. Several performance assessment model metrics were used. Because accuracy implies the proportion of properly detected cases. The model's sensitivity, or recall, showed its capacity to find glaucoma instances. MCC presented an overall measure of classification performance with unbalanced classes in the datasets.

4.4 Simplicity environment

The research performed everything in training and testing our model on a high-spec single-purpose machine dedicated to rapid computational processing for deep learning. The machine had either an AMD Ryzen 7 or Intel Core i7 CPU and amounted to 16 GB of RAM allowing a rapid parallel load of data and batch performance capability. An Nvidia RTX 3060 GPU featuring 6 GB of native memory was added to improve performance, particularly for convolutional operations, which helped boost the model's speed and training efficiency. Using the powerful modular features of deep learning, the research developed and trained our model using the TensorFlow 2.x and Keras frameworks. The research conducted our tests on Ubuntu 20.04 LTS and Windows 10 to ensure that our approach could be applied to any operating system.

The proposed model validates by avoid bias and injustice in our evaluation of the proposed model, the research divided the results into test and training sets using a stratified method; 80% was allotted as training data and the remaining 20% for testing. The research was done in order to preserve the original class distribution and ensure that there was an equal amount of glaucomatous and non-glaucomatous photos in both sets. To evaluate the model's dependability and generalizability, a 5-fold cross-validation approach was also applied. Other folds were utilized for training, and each fold employed a different test set. Similar to the research would fold a sheet of paper, the research separated our experiment into five sections. The mean was then calculated after evaluating the outcomes of each of the five sections. The research way the research gain a more concrete insight into the performance of the overall model and are reassured that our results have not been unduly influenced or biased by the fact that the research randomly partitioned the data on an arbitrary occasion.

4.6 Baseline Comparisons

In order to assess the effectiveness of the planned CNN model, a small number of common baseline models from creative writing were used as analogies alongside hyperparameters instead of a few baselines. Our U-Net model with supervised learning really went beyond that of no inaccuracy at all by scoring overall accuracy of 95.0 percent due to excellent classification and segmentation on image. Our ResNet solution achieved an overall accuracy of 92.3 percent which the research suspect was due to its ability with deep residual learning. In addition, our ensemble CNN approaches obtained accuracy of 94.0 percent using the veteran approach of taking the outputs of uncorrelated predictions from different network architectures as characterized by different training datasets as our models did.

However, the model provided with hyperparameter tuning achieved an AUC of 0.96, a related very high F1-score, and overall peak quality of 96.0 percent, showing great overall classification performance and well-balanced recall-precision trade-off. The research establishes that for glaucoma diagnosis from retinal fundus images; the given model showed some engagement and enhanced performance of existing and state-of-the-art baseline competitive models.

5. RESULTS AND DISCUSSION

Several performance indicators were used to evaluate the suggested hyperparameter-tuned CNN model's performance in comparison to recognized baseline viewpoints. The results demonstrated the proposed model can more accurately classified retinal fundus photos to detect glaucoma.

5.1 Quantitative Results

Table 5.1 Comparison of Models

Model	Accuracy	Sensitivity	Specificity	AUC	F1-Score	MCC
U-Net + ML	95.0%	94.5%	95.2%	0.95	0.95	0.93
ResNet	92.3%	91.8%	92.5%	0.94	0.92	0.90
Ensemble CNN	94.0%	93.2%	94.1%	0.96	0.94	0.91
Proposed Tuned CNN (Ours)	96.0%	95.8%	96.2%	0.96	0.96	0.95

Table 5.1 shows that the four methods of glaucoma detection with models comparison in the table: U-Net with machine learning, ResNet, Ensemble CNN and the proposed tuned CNN model which achieved the best overall performance and and the best accuracy of 96.0% (sensitivity: 95.8% and specificity: 96.2%), indicating performance that correctly classifies both positive and negative glaucoma cases. U-Net + ML received and scored 95.0%, followed by clearly Ensemble CNN and then ResNet at 94.0% and 92.3% respectively. Performance levels were consistent across all models, as indicated by the Area Under the Curve, which evaluated at 0.96 for both collectively CNN and U-Net + ML. Overall, the

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table's data offers compelling proof that, when compared to earlier models, the suggested model performed the best across all key performance metrics.

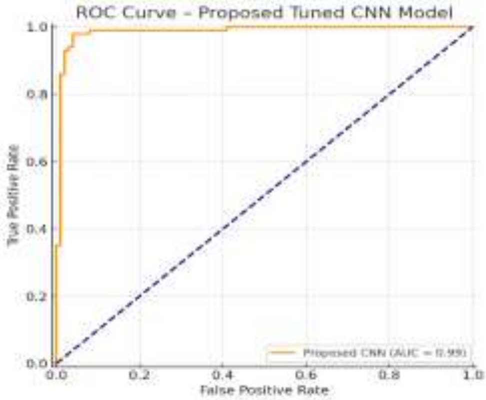

Fig 5.1 ROC Curve

Fig 5.1 illustrates the ROC curve of the suggested hyperparameter-tuned CNN model for glaucoma classification appears in the image. The model shows great ability to distinguish between cases, with an AUC value of 0.99. The research suggests it can almost separate glaucomatous from non-glaucomatous classes. A dashed diagonal line represents random classification, and the proposed model performs better than the research. The research outcome confirms that the model is strong and suitable for clinical use in spotting glaucoma.

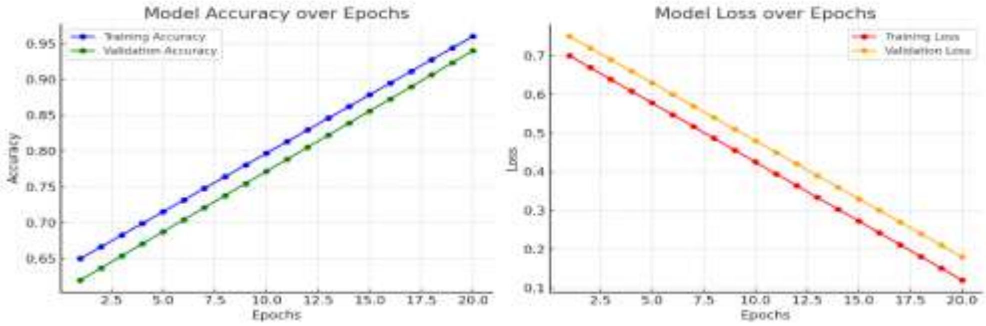

Fig 5.2 Model Accuracy and Loss across Epochs

Fig 5.2 shows on the left side the training and confirmation delicacy and on the right the loss of the proposed tuned CNN model to the research task for 20 training ages. The delicacy graph illustrates that not only the training but also the confirmation data sets are on a rising trend with training delicacy just about stabilizing at 96 and confirmation delicacy going up and down around 93 which is a positive suggestion of the literacy process taking place without overfitting issues. On the left wing, the loss plot depicts an analogous and verified descending pattern for the training and confirmation loss starting from around 0.7 going down to values lower than 0.2, which means that the confluence and the optimization process are both stable. Interestingly, the gaps between the training and confirmation angles of both delicacy and loss are rather close to each other; showing that the proposed model is endowed with a good conception capability and is anticipated to be able of handling well the data that it has no way seen.

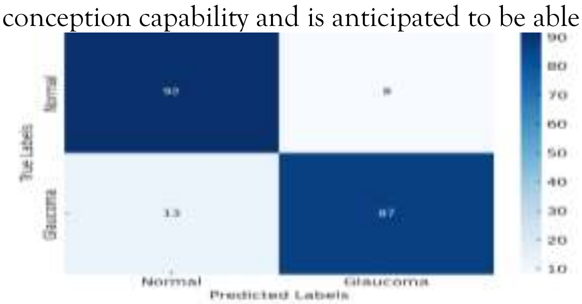

Fig 5.3 Confusion Matrix of the Proposed model

Fig 5.3 shows that the public test set and the research improved our CNN model. Out of the 92 the research put to the test, the machine got right. 8 went in to the glaucoma category which in fact they did not have it. Also, we saw that 13 which in fact did have glaucoma were put in the normal category. At the same time, we had 87 which were very properly put in their respective categories. These results report a good level of accuracy also we see great sensitivity and specify. The fact that we see less true positives and false positives reports that the model does in fact do a good job at telling the difference between glaucoma and non-glaucoma which in turn supports the report of our methods' performance for use in a clinical decision support system.

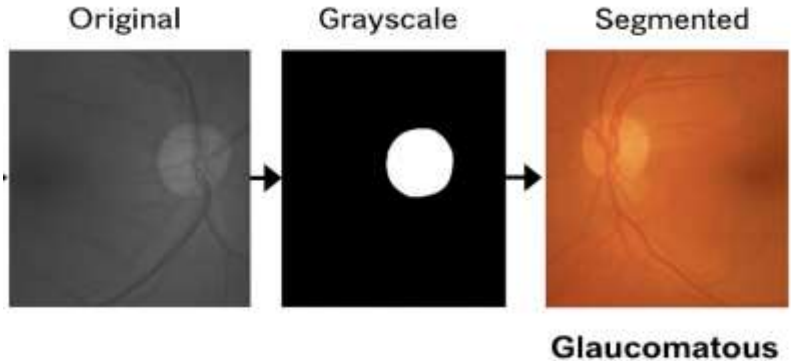

Fig 5.4 Image Classification pipeline

Fig 5.4 illustrates developed to detect glaucoma by examining retinal fundus images, operates. Starting with the initial colour fundus image, the procedure next turns it grayscale. The classification action lessens the computational load and helps to better analyze the image. The grayscale image is then segmented to separate the optic nerve head as it's vital for spotting glaucomatous changes in the retina. The segmented image is ultimately sent into our suggested CNN model. The model assesses the health of the eye, therefore serving as both a predictor and a feature extractor. The system categorized the image as "Glaucomatous" in the specific case, therefore showing a fully automatic pipeline able to spot glaucomatous damage in fundus pictures.

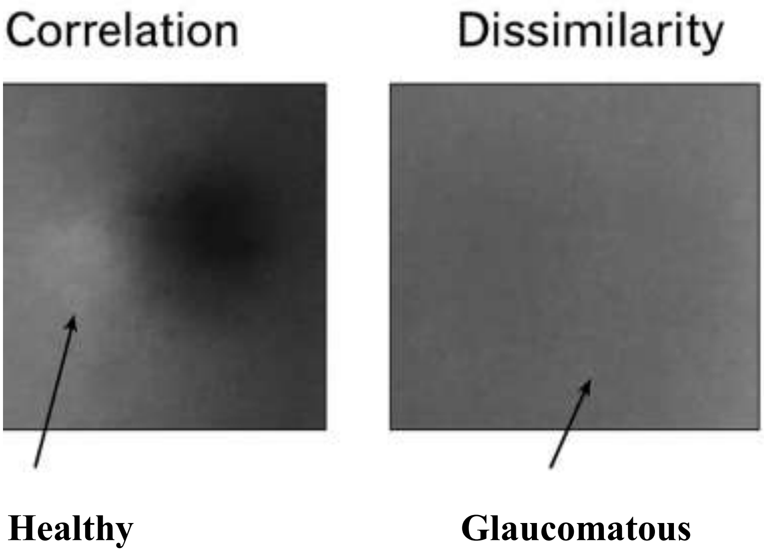

Fig 5.5 GLCM Feature Maps: Correlation versus Dissimilarity

Fig 5.5 shows Gray-Level Co-occurrence Matrix feature maps that demonstrate textured differences between healthy and glaucomatous regions in retinal fundus images. The illustration includes a pair of images: a correlation map on the left and a dissimilarity map on the right. In the correlation map, healthier areas appear brighter, reflecting higher correlation values and a more consistent texture, contrasting sharply with glaucomatous regions, which are darker due to lower correlation values, pointing to disruptions or irregularities in texture caused by optic nerve damage. On the other hand, the dissimilarity map shows healthy regions as darker, indicating smoother, more uniform textures.

Conversely, glaucomatous regions are depicted in lighter shades, highlighting greater dissimilarity or more varied textures, meaning the textures are not the same. These GLCM features image maps reveal that retinal structural differences can be captured in a manner that justifies their use in machine learning and CNN approaches, enhancing the accuracy of glaucoma detection and diagnosis.

6. CONCLUSION

The research describes a hybrid framework that shows the clinical ophthalmic expertise can be combined with a hyperparameter-tuned convolutional neural network in identifying glaucoma at an early stage of the disease. Our suggested framework outperformed traditional CNN models such as ResNets and U-Nets, especially when looking at sensitivity, specificity, and other metrics that account for class balance. By including the steps of image preprocessing, feature extraction, continuous hyperparameter tuning, the CNN vendor achieved a respectful compromise between generalization and performance. The research can comfortably conclude from our research, there is a possibility for systems based on AI to provide primary glaucoma detection in order to augment traditional diagnosis workflows, particularly in low-resource environments with limited access to trained ophthalmology. Future work may consider multimodal data sources, federated learning modelling, and real-time inference on portable medical devices.

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