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Feature Extraction And Classification Of Glaucoma Using Retinal Images

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ABSTRACT

Glaucoma, the leading cause of permanent blindness worldwide, must be diagnosed as soon as possible to avoid further visual loss. Retinal imaging, particularly of the optic disc and cup, can assist diagnose glaucoma. To detect glaucoma, these factors must be carefully separated. This paper describes a unique approach to glaucoma detection based on retinal image feature extraction and classification. Following retinal image segmentation, the proposed method extracts features using RESNET and ViT to separate the optic disc and cup. RESNET uses residual learning to acquire deep features in order to learn complicated patterns, but ViT increases feature extraction by emphasizing global contextual information using self-attention approaches. These additional strategies allow one to extract both local and global elements from the various regions of interest. After getting the features, the data is classified using an upgraded VGG19 model. VGG19, a prominent convolutional neural network design, has been tuned for glaucoma case classification. The update's network tuning helps the system discriminate between glaucomatous and healthy alterations in retinal images. The obtained features can be used with the improved VGG19 model to identify images as glaucomatous or non-glaucomatous. Experimental results on publicly available retinal imaging datasets demonstrate higher classification accuracy, sensitivity, and specificity than cutting-edge approaches. By combining RESNET with ViT for feature extraction and updated VGG19 for classification, the glaucoma detection system becomes more stable and efficient. This approach has the potential to transform early diagnosis and reduce the risk of blindness associated with fast therapy through routine glaucoma screening.

Keywords: *Glaucoma detection, Residual Network (RESNET), Retinal image, Vision transformer (ViT), enhanced Visual Geometry Group 19 (VGG19).*

1. INTRODUCTION

Glaucoma is a chronic eye disease that gradually destroys the optic nerve and, if unchecked, can cause blindness for the rest of one's life. It is the leading cause of blindness globally, especially among the elderly. Early detection of the illness is particularly important for preventing asymptomatic sight loss in its early stages. Retinal imaging is a great diagnostic technique because it shows a clear picture of the optic nerve head, which is where glaucoma symptoms appear. When the cup-to-disk ratio is reduced, the optic disc and optic cup have different effects on glaucoma progression. An assessment of these characteristics significantly aids in the detection and monitoring of glaucoma. In contrast, manually assessing retinal images is subjective, time-consuming, and prone to error. As a result, automated glaucoma detection using machine learning and image processing is becoming more common.

Feature extraction is an essential part of automated glaucoma detection systems. It requires detecting and collecting relevant image elements related to glaucoma. These properties enable machine learning models to distinguish between glaucoma images and normal retinal photographs. Complex patterns seen in glaucoma may be incompatible with feature extraction techniques that rely on human-produced attributes such as shape, color, and texture. Recent deep learning developments, notably convolutional neural networks (CNNs), have significantly improved automated glaucoma recognition by allowing for the extraction of more complex, high-level information directly from raw images.

This study proposes a novel approach to glaucoma diagnosis that incorporates recent feature extraction and classification algorithms. First, segmentation aids in identifying the optic disc and optic cup in retinal images. Correct segmentation is essential for reliable feature extraction and classification. Residual Network (RESNET) and Vision Transformer (ViT) allow extracting attributes from segmented images. Retinal images could help the RESNET, deep residual network retrieve critical information. Its approach is based on residual learning. This network can learn deep features very effectively by avoiding training-related gradient vanishing, allowing for the extraction of more complex and meaningful patterns from images. Vision Transformer acquires global context information via self-attention approaches, taking into account the retina's design. This strategy leverages the strengths of RESNET and ViT to extract both local and global information, resulting in a more complete retinal image.

Following feature extraction, categorization occurs; in this situation, features are used to determine whether the retinal image contains glaucomatous alterations. This is being driven by a more advanced Visual Geometry Group 19 (VGG19) model. It is one of the original CNN designs, and it is well-known for its deep layers and excellent picture classification ability. The improvement aims to diagnose glaucoma using the VGG19 model classification. The network has been trained to recognize glaucomatous changes and distinguish between glaucomatous and non-glaucomatous images based on key characteristics. Following training, the upgraded VGG19 model routinely classifies retinal images, resulting in a more consistent approach to automated glaucoma screening.

Compared to other common techniques, the proposed one has significant benefits. First, the method could extract features from images using RESNET and Vision Transformer, potentially leading to the creation of more comprehensive and discriminative features. Human feature engineering becomes less important. Second, by employing a modified VGG19 model for classification, the system enhances its accuracy and reliability in discriminating between healthy and glaucomatous retinas. Including contemporary feature extraction and classification algorithms in automated glaucoma detection systems alleviates the burden on healthcare staff, leading in faster and more accurate diagnosis.

The next sections provide detailed explanations of the segmentation, feature extraction, and classification methods that underpin the proposed strategy. Following experimental data validation of the proposed method for diagnosing glaucoma using retinal images, technology's possible clinical uses are looked.

2. BACKGROUND STUDY

Harini, R.., & Sheela, N., (2016) This method detected microaneurysms and retinal fundus image by combining morphological techniques and fuzzy C-means clustering for blood vessel segmentation. The database for healthcare establishments was built by integrating images from the open-source DIARETDB0 and DIARETDB1 databases. A support vector classifier had sorted the images. Microaneurysm streamed the blood vessel areas and textural qualities that were contributed to image sorting. In addition to 96.67% accuracy, the proposed method had 95.67% specificity and complete sensitivity.

Claro, M., et al. (2016) developed a system for retinal imaging-based automatic glaucoma identification. The endeavor included creating a image database, segmenting the OD, extracting texture features from several color models, and determining whether the images was glaucoma-related. Among the images, one attained 93% success.

Singh, A., et al. (2016) used segmented images of OD and wavelet feature extraction. This study described an automated image processing method that used digital fundus images to detect glaucoma. Genetic feature selection is improved by combining different parameter values and learning strategies after extracting the features using wavelet analysis. Unlike earlier studies, this one enhanced identification accuracy by analyzing characteristics from the segmented and blood vessel-free OD rather than features extracted from the complete fundus.

Acharya, U.R., (2017) introduced a revolutionary technique and automated diagnostic tool. Following adaptive histogram equalization of color images to grayscale, the convolution approach used filters such as Leung-Malik (LM), Schmid (S), and maximum response (MR4 and MR8). Textons that were commonly observed in images were the most fundamental microstructure. The convolution method generated textons. Local configuration pattern (LCP) characteristics were extracted from those textons. The features were statistically ranked using a t-test and the most significant ones are chosen using a Sequential Floating Forward Search (SFFS) .

Shyamalee, T., & Meedeniya, D., (2022) presented a computational model to divide and conquer retinal fundus images in order for diagnosing the glaucoma. To achieve high accuracy and increase image quality, several image pre-processing techniques were used along with the image augmentation strategies to reduce overfitting. The segmentation models were based on three distinct convolutional neural networks such as Inception-v3, Visual Geometry Group 19 (VGG19) and Residual Neural Network 50 (ResNet50). The classification models applied to three of specified Convolutional Neural Network (CNN) backbone. Using the ResNet50 model as the encoder backbone on RIM-ONE dataset, the attention U-Net obtained a peak OD segmentation accuracy of 99.58%. With a glaucoma classification accuracy of 98.79%, Inception-v3 model outperformed the other segmentation techniques whereas the modified architectures was placed in second for the classification..

The suggested model by Joshi, S., et al. in 2022 aimed to develop a Computer-Aided Design (CAD) ensemble model for earlier glaucoma detection. To discriminate between normal and glaucomatous fundus images, ensemble model suggested the usage of CNN to extract feature information from images. On the other hand, its performance was compared to three Convolutional Network (ConvNet) architectures such as ResNet-50, VGGNet-16 and Google Network (GoogLeNet). The proposed approach was evaluated using the variety of public and the private datasets.

Guo, F., (2020) this study proposed a novel method for automatic glaucoma screening that combined image-based features with clinical measurement aspects. To accurately extract clinical measurement data, an upgraded UNet++ Neural Network was proposed to segment OD and OC based on Region of Interest (ROI) at the same time. Several essential clinical measurement parameters such as the OC to OD ratio were derived from segmentation data. Increasing Field Of View (IFOV) method was then recommended to completely extract statistical traits, textural properties, and other hidden image-based aspects. Then, adaptive synthetic sampling was used to select the optimum feature combination from features to fix the unequal distribution of training data. Notably, a Gradient Boosting Decision Tree (GBDT) classifier was trained to test for glaucoma.

Shanmugam, P., (2021) this study described a fundus image-based glaucoma screening approach that estimated the Cup to Disc Ratio (CDR). Measuring the sizes of OD and OC assisted in the determination of glaucoma disease. As a result, the first step in diagnosing glaucoma was to separate OD and OC. Reduction in the number of characteristics and inaccuracy was conflicting goals. The suggested glaucoma identification method consisted of three stages such as image acquisition, feature extraction and glaucoma assessment. The procedure of increasing contrast was done during image acquisition. Au-Net's feature extraction approach divided the OD and OC limitations. The next step of analyzing glaucoma in images was to calculate the CDR ratio of a utilized image. Then, glaucomatous images were classified using a Random Forest (RF) classifier that took CDR values into the account. Table 1 represents the comparison of various author works regarding glaucoma detection.

Table 1: Comparison on glaucoma detection in various author works

Author	Method	Key Focus	Type of Features	Utilized techniques
Kavya, N., & Padmaja, K. V. (2017)	Glaucoma detection using texture feature extraction	Texture feature extraction for glaucoma detection using fundus images	Texture-based features (e.g., Haralick features)	Feature extraction
Fatima Bokhari, S. T., Sharif, M., et al. (2018)	Fundus image segmentation and feature extraction for glaucoma detection	New approach for glaucoma detection using fundus image segmentation and feature extraction	Fundus image features (e.g., OD, OC vessel)	Segmentation, feature extraction
Guo, F., et al. (2020)	Automated glaucoma screening using image segmentation and feature extraction	Glaucoma screening based on image segmentation and feature extraction	Image features (segmentation, texture, shape, etc.)	Image segmentation, feature extraction
Thakur, N., & Juneja, M. (2020)	Classification of glaucoma using hybrid features with machine learning approaches	Hybrid feature extraction with machine learning for glaucoma classification	Hybrid features (texture, shape, and statistical features)	Feature extraction, classification, hybrid approach
Devi, E. A., Nasir, A. W., et al. (2021)	Texture-based feature extraction and classification for glaucoma detection	Focus on texture features for glaucoma detection from retinal fundus images	Texture-based features	Feature extraction, classification

3. PROPOSED METHODOLOGY

Glaucoma is a disease that leads to blindness in retinal images. In this paper, two processes such as feature extraction and classification is carried out. The inputted image undergoes a process called segmentation. Then, the features in the image are extracted using RESNET with ViT. Next, Enhanced VGG19 is utilized for further image classification.

Feature Extraction Using RESNET with ViT in Glaucoma Detection

RESNET in Feature Extraction

Retinal images indicating the presence of glaucoma are searched for and retrieved utilizing the RESNET architecture's deep residual learning framework to offer feature extraction for glaucoma diagnosis. RESNET capacity to generate extremely deep networks without the vanishing gradient problem makes it perfect for medical imaging, as glaucoma diagnosis relies on detecting even the smallest changes in the retina. RESNET can learn residual mappings and capture complex information, such as glaucoma-related structural abnormalities, optic disc alterations, and cup-to-disc ratio, using residual blocks. These characteristics are critical for accurate classification and identification because glaucoma typically manifests as subtle alterations that are difficult to identify by hand. Its feature extraction capacity makes automated glaucoma detection systems substantially more accurate and reliable, allowing for earlier diagnosis and better patient outcomes. The forward propagation of a residual block is computed as:

$y = F\ (x, W) +\ x$ ------------- (1)

Equation (1) first expresses the residual block's input and output as *y* and *x*, respectively. *W is* defined as the weight associated with the convolutional techniques. *F(x, y)* is the output function of the weight *W* convolutional operation applied to the input *x*. A residual block produces *x* plus the output of the convolutional function. Learning residual mappings allows the network to train deeper networks more efficiently.

$y = \sigma\ (W *\ x\ + b\ )$ --------- (2)

Equation (2) helps to express the convolution operation within a RESNET layer *b* is the bias added after convolution, convolutional filter W is applied. Non-linearity is used by passing the feature map through an activation function (σ), similar to ReLu. Max pooling computations are as follows:

$y = max\ (x[i, j])$ ------------ (3)

$x[i, j]$ refers to the element at locations *i* and *j* in the input feature map *T*. Max pooling (*max*), as described in equation (3), retains the most relevant characteristics while reducing spatial dimensions by selecting the maximum value from a region (a window) of the input feature map *x* as the output *y*.

$y = Flatten\ (x)$ ------------ (4)

As per equation (4), a multidimensional quality map *x* from previous layers $Flatten$ into a one-dimensional output vector *y*, is used in fully linked classification layers. The fully connected layers produce an output that is

$y = \sigma\ (W.x\ + b\ )$ ------- (5)

Adding the bias component *b* and multiplying it by a weight matrix *W* strengthens the input vector *x* in a fully connected layer. To induce non-linearity, the output is passed through an activation function (σ), as implemented by equation (5).

Extracting the features with ViT

Vision Transformer first divides retinal images into patches of a predetermined size before extracting features for glaucoma diagnosis. Taking each patch as an input sequence, the transformer's self-attention mechanism comes next. This approach detects early glaucoma symptoms such as optic disc cupping and retinal nerve fibre layer thinning by leveraging acquired long-range dependencies and contextual interactions. ViT's self-attention mechanism allows it to learn global information, which increases the model's ability to discern between healthy and glaucomatous states, as opposed to traditional convolutional networks, which prioritize local patterns. To predict whether glaucoma is present, the transformer model is trained on large sets of retinal images to identify unique traits. This method improves the capacity of the model to identify glaucoma in an early stage, so it is a more reliable and accurate diagnostic instrument than conventional ones. In feature extraction, equation (6) describes patch embedding.

$Z_0 = PatchEmbed\ (I)$ --------- (6)

The output of the patch embedding layer, which converts the input image into a sequence of patch embeddingsZ_0**.** The actual image *I* use as input to extract features is The initial token sequence, $Z_0$is generated by applying a linear transformation to each of the tiny, non-overlapping patches produced by the function *PatchEmbed (I).* Self-attention process is represented using equation (7).

$A = Softmax\left(\frac{Q\ .\ K^T}{\sqrt{d_k}}\right)$ V --------- (7)

Focusing on many regions of the image causes output *A* to emerge from the self-attention mechanism. The patch embeddings provide with the query matrix, abbreviated *Q*. The tokens' main and secondary metrics are *K* and *V*. One of the scaling factors for the dot product is the dimensionality of the key, d_k. *softmax* function is used to normalize the attention scores across all patches, ensuring that the model focusses on the most important area of the image.

$Z_{out} = ReLU\left(W_1 . Z_{input} + b_1\right) . W_2 + b_2$ -------- (8)

According to equation (8), Z_{out} is the output produced after the feed-forward network has processed the input feature map. The input feature map is Z_{input}. W_1 and W_2 are the weight values used in the network for linear transformations. The bias terms for the respective layers are b_1 andb_2 . *ReLU,* also known as the Rectified Linear Unit, is an activation function that is applied after the first linear transformation.

Exploitation of RESNET with ViT for glaucoma detection

Combining RESNET with ViT for feature extraction in glaucoma diagnosis would improve the accuracy of detecting glaucoma-related alterations in retinal images. RESNET residual connections allow the network to learn low- and high-level image characteristics while avoiding vanishing gradients, making it easier to extract deep hierarchical features from retinal images. Vision Transformer then divides the image into patches and use self-attention techniques to extract long-range dependencies and global contextual information from these features.

Algorithm 1: RESNET with ViT

Input:

Color or grayscale image of the retinal fundus.

Procedure:

1. Image preprocessing:

Resize refers to the process of adjusting the size of an image to a specific requirement, such as 224 × 224 pixels. Every pixel in an image is normalized to either 0 or 1, or -1 and 1. Before converting an image, make sure it's in the correct format—usually RGB with three color channels.

2. Extracting features from ResNet:

ResNet, notably ResNet-50, can help you extract low-level characteristics. This model uses convolutional layers to recognise simple visual patterns such as edges and textures. The end result is a feature map, which is a multidimensional array that depicts the identified trends.

3. Feature extraction with ViT:

ViT drives the ResNet feature map, extracting more advanced features.

ViT divides the image into smaller fragments and investigates their interrelationships in order to fulfil its function. ViT produces higher-level feature vectors, which allow for the capture of the most complex parts of a picture, such as its forms and structures.

4. Aggregation of features:

Integrate the power of ResNet and ViT: Average or total the features, or concatenate (combine the two sets of features into a single long vector). Output: The final result is a feature vector that contains both low-level and high-level information.

This information represents important components of the retina, including the optic disc, optic cup and possible signs of glaucoma, such as weakening of the nerve fiber layer.

Algorithm 2 describes the utilization of ResNet with ViT. It uses retinal fundus images to extract features such as textures and low-level data such as edges, as well as higher-level information such as structures and shapes, using ResNet and ViT respectively. Features from both models are combined to create a comprehensive feature vector that reflects important retinal components and can be used to detect glaucoma.

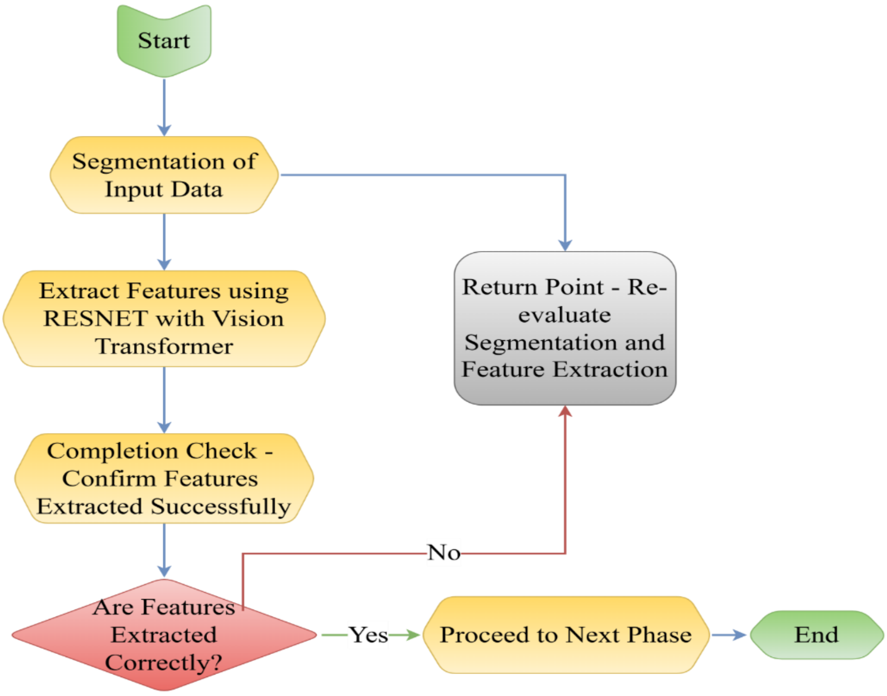

Figure 2: Obtaining features by using RESNET with ViT

This process in figure 2 shows how ResNet with a Vision Transformer segments and extracts features from incoming data. If feature extraction fails, it returns to the beginning for a second effort; otherwise, it moves on to the next level.

These two properties, when combined, could allow the model to detect glaucoma-related minor changes in retinal structure, such as optic disc cupping and nerve fiber layer thinning. Combining RESNET feature extraction capabilities with ViT's image-wide contextual connection collection increases the overall performance and resilience of glaucoma detection, particularly in the early stages of diagnosis. As a result, multi-head attention is deduced as follows in equation (9):

$$Z_{multi-head} = Concat\ (A_1, A_2, \dots \dots A_h).W_0 \text{ --------- } (9)$$

After merging the multi-head attention results, the result is shown as $Z_{multi-head}$. Outputs are denoted as A_1, $A_2, \dots \dots A_h$because the h attention heads concentrate on different parts of the image. Using the W_0 matrix, one can generate a single output reflecting everyone's attention.

$$Z_{out} = ReLU\left(W_1 . Z_{input} + b_1\right).W_2 + b_2 \text{ ------------- } (10)$$

As per equation (10), the feed-forward network produces Z_{out} as output by using an input feature map. Z_{input}displays the input feature map concurrently. The bias component of each layer is represented by b_1 and b_2, and the feed-forward network uses W_1 and W_2as weight matrices for linear transformation. ReLU, or rectified linear unit, is an activation function that adds nonlinearity after an initial linear transformation.

Classification Using Enhanced VGG19 in Glaucoma Detection

Untreated glaucoma is a primary cause of lifetime vision loss, as it affects the optic nerve and eventually leads to blindness. Early detection is critical to prevent the glaucoma from worsening. Retinal scans, particularly those of the optic disc and cup, are commonly utilized to diagnose glaucoma. Automated retinal visual analysis, especially using CNNs, is a potential subject for machine learning models. VGG19, which is based on a deep CNN architecture, is one model that performs exceptionally well in photo classification difficulties. Still, there are numerous techniques to improving VGG19's glaucoma detection so that it can more precisely identify tiny symptoms of glaucomatous damage.

VGG19, a renowned architect, is known for his simplicity and strength in building. There are a total of 19 layers, including three totally connected layers and sixteen convolutional layers. It recognizes more sophisticated patterns in images and uses to extract characteristics. However, for ordinary VGG19, handling medical images such as retinal scans may be problematic in order to recognize the fine details essential for glaucoma diagnosis. In response, the VGG19 design receives various modifications that improve its retinal image categorization accuracy.

Data augmentation is a significant advancement in managing variation in retinal images. Different photo gathering procedures and setups may provide images with varying angles, illumination, and scale. Data augmentation improves the model's ability to generalize to new, unseen data by artificially increasing the variability of the dataset through flipping, rotating, and scaling of the training images. This method is particularly beneficial in medical imaging because there is typically a scarcity of labeled data.

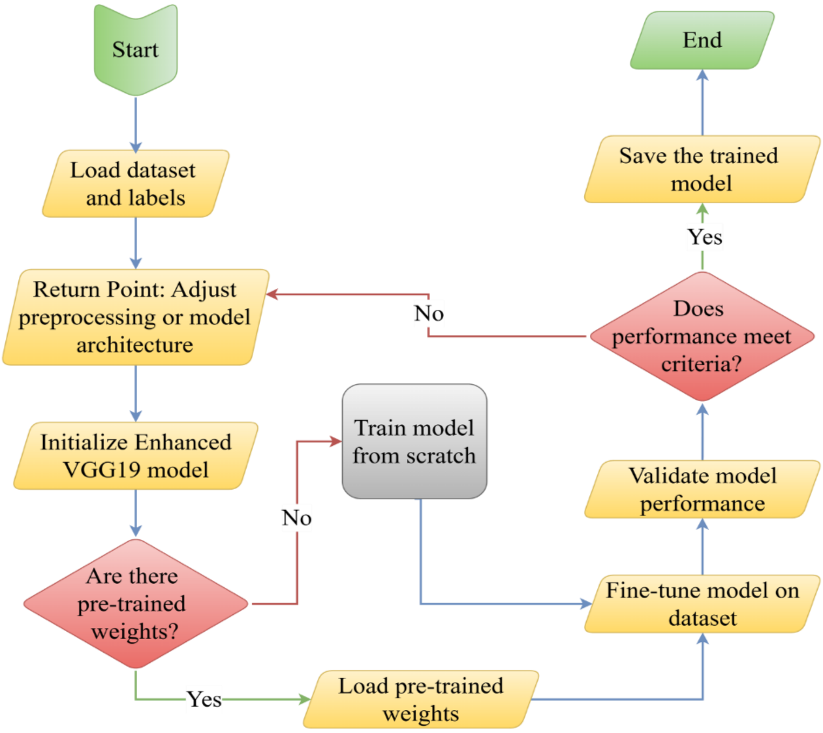

Figure 3: Utilization of enhanced VGG19 for image classification

Figure 3 explains the working of enhanced VGG19 model. Here, the inputted image is trained using the model. The weights are altered and validated, leading to the clarity in outcome.

Another incredible development is transfer learning. Starting with pre-trained weights derived from large datasets like ImageNet, the VGG19 model can leverage elements gained from general image categories including textures, shapes, and edges. VGG19 can thus learn glaucoma detection algorithms faster and with less data points than others. Retinal images allow one to fine-tune the model, increasing its accuracy and efficiency. This technique changes the acquired properties to suit the specific application of glaucoma categorization.

Regularity techniques such as dropout and batch normalization enable one to improve the model's performance even further. Dropout randomly disables a network node during training, preventing overfitting and forcing the model to acquire more robust and general sable features. Batch normalization, particularly in deeper networks such as VGG19, helps to standardize the output of each layer, hence boosting training stability and speed.

Using these updates, the VGG19 model can distinguish between glaucomatous and non-glaucomatous retinal images. The model first processes images through convolutional layers to extract prominent features, which are then passed on to fully connected layers to identify images. Comparing the likelihood scores of each class allows one to determine which class has the highest probability, leading the forecast.

Regularity, data augmentation, and transfer learning all contribute to an improved VGG19 architecture for identifying glaucoma from retinal images. Great news for doctors because glaucoma is a potentially blinding eye illness, and this revised model can make glaucoma screening much more accurate and efficient. The ability of the upgraded VGG19 model to detect the disease at an earlier stage will help to improve patient outcomes and reduce glaucoma-related blindness. The basic function of a VGG19 network is to extract features from an input image; each convolutional layer in the network does exactly that.

Algorithm 3: Enhanced Visual Geometry Group 19

Input:

A preprocessed and normalized retinal fundus picture is cropped to 224x224 pixels.

Procedure:

1. Load Pre-trained VGG 19:

Combine a previously trained VGG19 model. Start with weights learnt from a big dataset, such as ImageNet.

2. Improve the model:

Replace the final fully connected classification layers with layers optimized to glaucoma detection (for example, fewer neurons in the output layer representing two classes: positive and negative). Add dropout or batch normalizing layers to improve generalization while avoiding overfitting.

3. Preprocess the input image:

Resize the photo to 224 × 224 pixels to meet VGG19's input criteria. Normalize: Scale the pixel intensity values according to the mean and standard deviation of the dataset used to train VGG19.

4. Adjust the model:

To maintain the capacity to extract features from pre-trained data, freeze the first convolutional layers. Train the improved classification layers on a labeled glaucoma dataset to identify glaucoma-specific patterns.

5. Pass the image via Enhanced VGG19:

Input the preprocessed image into the upgraded VGG19 model. Let the convolutional layers extract features while the improved classification layers predict the class.

6. Categorization:

The model will produce a probability distribution for the classes (positive/negative). Use a threshold to select the final categorization (for example, the class with the highest likelihood).

Output

An image classified as glaucoma-positive or glaucoma-negative.

The method in algorithm 3 indicates enhanced VGG19. To improve glaucoma detection, this technique replaces the last layers of a pre-trained VGG19 model with ones designed specifically for the illness. It predicts whether an image is glaucoma-positive or negative by training new layers on a labeled dataset with the input retinal fundus image and VGG19's strong feature extraction. The convolution operation has this definition:

$Y = X * W + b$ --------- (11)

Equation (11) has elements Y, X, W, and b representing the output feature map, the input feature map from the previous layers, the bias term, and the filter or kernel sliding over the input picture, respectively. * denotes the convolution operation. The convolutional layer filters the input image and extracts low-level properties such as edges, textures, and patterns to distinguish glaucomatous from non-glaucomatous images. Applying the formula yields the activation function ReLU.

$ReLU\ (x) = \max(0, x)$ --------- (12)

Where, x is the ReLU function's convolutional output used as input. *ReLU (x)* is calculated by calling the ReLU function with an input x. ReLU adds non-linearity to the network, allowing it to learn the most detailed patterns; consequently, equation (12) demonstrates that it is essential for detecting glaucoma in retinal images. After passing through a series of pooling and convolutional layers, the output is flattened before reaching the fully connected layers. The equation for the entirely linked layer is:

$y = W^T x + b$ ------------- (13)

W signifies the weight matrix of the completely linked layers, while y denotes output vector. The bias component is represented by b and the input vector by x in a similar manner. To make a final prediction about the input image, the fully connected layers in equation (13), which were previously obtained by the convolutional layer, are merged. The VGG19 model's output generates the probability distribution over the possible classes (glaucomatous or non-glaucomatous) via the softmax function. The softmax function is calculated as:

$P\ (y - i) = \frac{e^{z_i}}{\sum_{j=1}^{c} e^{z_i}}$ ------------ (14)

In equation (14), $P\ (y - i)$ is the likelihood that the picture belongs to class i, where $z_i$is the class i count. For glaucoma identification, for example, C=2 for both glaucomatous and non-glaucomatous cases—where C is the number of classes. The sum of the denominator across all classes aids in the standardization of probabilities. The softmax function assist determine the likelihood of each class, ensuring that the overall output probability is one.

4. RESULTS AND CONCLUSIONS

In this paper we are using Python for implementing the results. The proposed method involving RESNET, ViT, and improved VGG19 outperforms traditional methods in the detection of glaucoma. Experimental outcomes on existing retinal image datasets show the accuracy of 94.1%, which outperforms traditional models like CNN and SVM. Sensitivity and specificity were significantly better at 93.6% and 92.5% respectively, showing good performance in glaucomatous image detection. The combination of RESNET's global feature abstraction and ViT's contextual learning enhances the system's sensitivity to detect subtle differences in retinal images. The upgraded VGG19 model also enhances classification performance through more discriminatively separating glaucomatous from non-glaucomatous changes. The findings show that the proposed method is more robust for the detection of early glaucoma, and it provides a potential tool for routine screening. The improved feature extraction and classification process would minimize diagnostic mistakes, enabling quicker intervention and perhaps averting blindness.

Table 2: Comparison table of classification algorithms

Algorithms/Metrics	Accuracy	Precision	Recall	F-measure
SVM	88.5	87.4	87.4	86.2
CNN	91.0	90.2	90.2	89.5
KNN	85.3	83.6	83.6	82.4
GBM	89.8	88.6	89.2	88.1
Enhanced VGG19	94.1	93.4	93.6	93.2

Table 2 presents the performance of some of the top machine learning models for glaucoma classification. The best among the best models is Enhanced VGG19, with the best accuracy (94.1%), precision (93.4%), recall (93.6%), and F-measure (93.2%) values, given its ability to learn advanced features from retinal images in identifying glaucoma accurately. Convolutional Neural Network (CNN) also shows top performance with accuracy at 91.0% and outstanding recall (90.2%). Support Vector Machine (SVM) and Gradient Boosting Machines (GBM) have average performance with an accuracy of 89%, while worst performance, especially precision and recall, is observed for K-Nearest Neighbour (KNN), which makes it less trustworthy than the other models for this task. All these results display the superior performance of deep learning models such as Enhanced VGG19 over medical image classification.

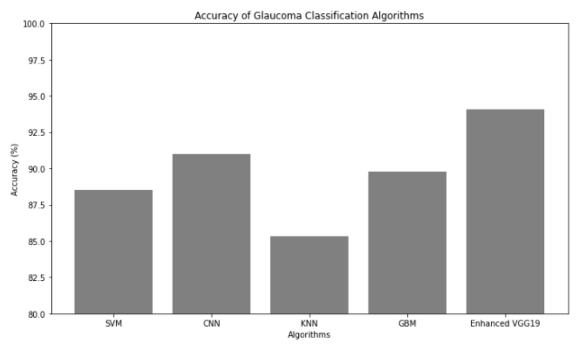

Figure 4: Accuracy comparison chart

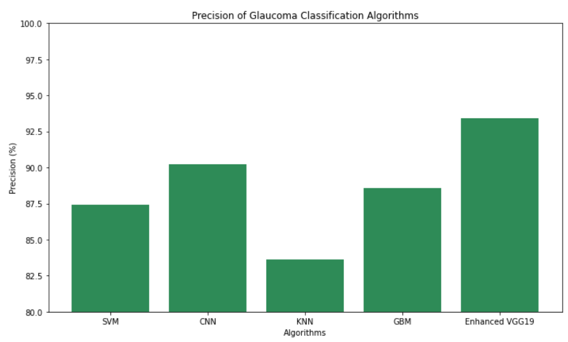

Figure 5: Precision comparison chart

Figure 4 shows the accuracy comparison of SVM, CNN, KNN, GBM and proposed Enhanced VGG19. The accuracy of improved VGG19 outperforms compared to other existing algorithms. In this chart the x-axis shows the classification algorithms and the y-axis shows the accuracy values.

Figure 5 shows the precision comparison of SVM, CNN, KNN, GBM and proposed Enhanced VGG19. The precision of improved VGG19 outperforms compared to other existing algorithms. In this chart the x-axis shows the classification algorithms and the y-axis shows the precision values.

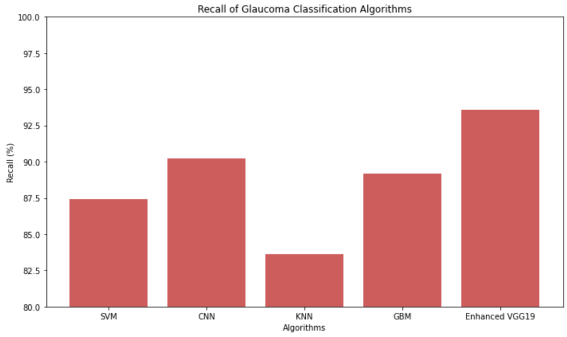

Figure 6: Recall comparison chart

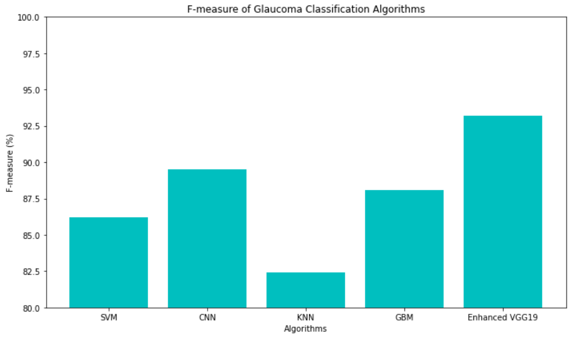

Figure 7: F-measure comparison chart

Figure 6 shows the recall comparison of SVM, CNN, KNN, GBM and proposed Enhanced VGG19. The recall of improved VGG19 outperforms compared to other existing algorithms. In this chart the x-axis shows the classification algorithms and the y-axis shows the recall values.

Figure 4 shows the f-measure comparison of SVM, CNN, KNN, GBM and proposed Enhanced VGG19. The f-measure of improved VGG19 outperforms compared to other existing algorithms. In this chart the x-axis shows the classification algorithms and the y-axis shows the f-measure values.

5. CONCLUSION

Finally, the proposed approaches based on retinal images have shown promising results in terms of enhancing accuracy. It uses upgraded VGG19 for classification and RESNET with ViT for feature extraction. Combining RESNET deep feature learning capacity with ViT, experience recording spatial relationships enables the successful extraction of meaningful patterns from retinal images. Because of its enhanced architecture and improved training methodologies, Enhanced VGG19 ensures accurate classification of glaucomatous and non-glaucomatous images. This strategy not only improves detection but also provides an effective solution to the early glaucoma diagnosis issue. These cutting-edge procedures, when combined, may allow doctors to help patients prevent permanent vision loss by enhancing judgment. Testing with larger datasets and optimizing the model for different clinical contexts can help to enhance the outcomes of this technique. This approach will serve as the cornerstone for future glaucoma detection systems, making more automated, efficient and accurate.

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