Journal of Research and Innovation in Technology and Management (JRITM)
Vol. 1 Issue 6, October 2024

Deep Learning-Based Glaucoma Detection & Interdisciplinary Retinal Image view point Analysis for Eye Disorders using Convolutional Neural Networks

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Abstract— Digital images are obtained from the retina and graded by trained professionals. Progression of diabetic retinopathy is assessed by its severity, which in turn determines the frequency of examinations. However, a significant shortage of professional observers has prompted computer assisted monitoring. The condition of the vascular network of human eye is an important diagnostic factor in retinopathy. A condition that affects eye vision is called glaucoma. This sickness is recognized as the irreversible condition that results in the vision deterioration. Many models for deep learning (DL) have been established for the appropriate detection of glaucoma so thus far. So this study gives architecture for the proper deep learning-based glaucoma detection by utilizing the CNN (convolutional neural network).The Inter disciplinary project proposes the Retinal image analysis through efficient detection of vessels and exudates for retinal vasculature disorder analysis. It plays important roles in detection of some diseases in early stages, such as diabetes, which can be performed by comparison of the states of retinal. The aim of this interdisciplinary paper is to develop an artificial intelligence model that accurately classifies whether a patient is affected by glaucoma using fundus eye images. This will be achieved through deep learning techniques, specifically leveraging convolutional neural networks (CNNs) to analyze the intricate patterns and features in retinal images.

Keywords— Glaucoma Detection, Deep Learning, CNN (Convolutional Neural Network), Artificial Neural Network (ANN)

INTRODUCTION

Retinal vessel segmentation are the implementation of screening programs for glaucomatic retinopathy, evaluation of the retinopathy of prematurity, detection of macular a vascular regions, detection of arteriolar narrowing, measurement of vessel tortuosity to characterize hypertensive retinopathy, measurement of vessel diameter to diagnose hypertension, cardiovascular diseases, and computer assisted laser surgery. Other indirect applications include automatic generation of retinal maps for the treatment of age-related macular degeneration, extraction of characteristic points of the retinal vasculature for temporal or multimodal image registration, retinal image mosaic synthesis, identification of the optic disc position, and localization of the fovea. Furthermore, the network of retinal vessels is distinctive enough to each individual and can be used for biometric identification, although it has not yet been extensively explored. Vessels, fovea, and optical disk are the three most important structures of the human retina and are mostly used for several applications, such as retinal image registration, illumination correction, as well as pathology detection inside the retina. Detection of these important structures manually is time consuming and depends on the expertise of the user.

The segmentation of blood vessels from fundus photographs can be difficult for a number of reasons. For accurate detection, the system employed a variety of Deep Learning algorithms. As mentioned, early identification can save a person's vision and avert blindness in humans. Therefore, in order to detect this sickness, the proper detecting model is needed. Many efforts have been made to construct a system like this. Additionally, a method for identifying the patients' glaucoma pattern is described. The method that is going to be given will classify the patterns that are detected in patients using the CNN methodology. The CNN model will be used to distinguish between the trends in the founded data for the purpose of glaucoma detection. For accurate illness identification, the total architecture consists of six levels. A dropout mechanism is also used in the process that is being offered to enhance the effectiveness of the suggested strategy. Finding the patterns that most closely resemble those of the healthy human eye and the glaucoma-infected eye is the main goal. Some of the corrupting sources are related to the acquisition process and kind of imagery, and others are intrinsic features of retinal image. So, Aim of the inter disciplinary project is to create an artificial intelligent model which classifies glaucoma is affected or not using fundus eye images with deep learning technique.

GLAUCOMA DETECTION

The ocular specialist looks for evidence of this condition in human eyes at least five times. The medical diagnoses that are examined in order to approve glaucoma are listed below.

a. Tonometry: This measures the pressure inside a patient's eye.
b. Optical Coherence Tomography: This scan is necessary to determine glaucoma diagnosis. It is utilized to identify retinal nerve fiber layers around the optic nerve, a significant indicator of early glaucoma damage.
c. Ophthalmoscopy: This test looks at the optic nerve. Given that glaucoma is a serious condition involving the optic nerve, this examination is crucial. Eye drops are used to make the patient's pupil larger so that a clearer view of the optic nerve is possible in order to look for indications of disease-related loss of nerve cells in the eye.
Perimetry: In the early stages of the disease, glaucoma causes loss of peripheral vision. Thus, the purpose of this test is to identify visual loss. Another name for this exam is the visual field test. It involves examining each eye separately using an automated gadget that illuminates lights in the subject's peripheral vision.

e. The test for the ophthalmic fluid outflow outflow angle is called a gonioscope. The fluid in the eye is constantly being prepared before flowing out at predetermined angles. This test is performed to determine whether angle-closure glaucoma, which is a blocked angle that causes high eye pressure, or an open angle that isn't functioning properly, is the source of the high eye pressure.

LITERATURE SURVEY

(Anna Paola Carrieri et. al, 2021) [1] Have devised an approach called logical artificial intelligence (XAI). Inferring microbial signatures affiliated with each trait and aptly predicting a variety of phenotypes from the leg skin microbiome, The study yielded a variety of results, such as age, epidermis moisture, and, most unexpectedly, menopausal and smoking status. This demonstrates the ability of explainable AI. They also considered using skin hydration model on a second, an impartial cohort will be used to evaluate the model's predictive and explanatory capabilities.

(Erico Tjoa et. al, 2021) [2] has discussed that AI and ML models have demonstrated outstanding performance across a range of disciplines. But because there is a great need for accountability and openness in the medical industry, In order to substantiate the veracity of machines' decisions and predictions, it is imperative to offer explanations.
They collected data from studies on the interpretability of machine learning algorithms or computer algorithms in general, categorized them, and then used the same categories for interpretability in the medical area. In particular, the objective of the category is to offer clinicians and practitioners a perspective on the utilization of interpretable algorithms that are available in a variety of formats.
(Eduardo Pinos-Velez, et.al, 2024) [3] have implemented the ancillary tools for identifying and analyzing human eye medical pictures to help in the provisional diagnosis of glaucoma. They focused on biomedical image processing to identify the characteristics regarded most significant within pictures collected from the back of the eye in order to diagnose glaucoma, a disorder that predominantly affects the physical statistics of the cup and the optical disc.

(Cyras et. al, 2022) [4] have provided a fascinating review of AF-based explanations, which use strategies and tactics that come from the field of computational argumentation to explainable AI models. In this study, the term model refers to a wide variety of areas, such as planning, LP tools, decision support, and recommender systems.The poll begins by outlining the various kinds of argumentation explanations and categorizing them as either intrinsic or post-hoc complete and posteriori approximate explanations have been created from the posteriori explanations. What the model describes, and the reasoning framework employed to complete the task is at the center of the survey.

(Kashif Siddiqui et.al, 2024) [5] have talked about how trustworthy AI in medicine is. In their research, a framework was developed to assess the credibility of AI in medicine in connection to common stockholders in the development of medical devices. The evaluation of a set of explainable AI (XAI) methodologies, they investigated AI models. The four components of trust—explainability, verifiability, fairness, and robustness—have been defined.
(Maede Zolanvari et.al, 2022)[6] highlighted the issue concerning AI, which makes it challenging for researchers and industry specialists to explain the choices made by advanced AI algorithms since we (as AI users) are unable to completely understand the components that go into such "black boxes"' decision-making.
. They emphasized the significance of integrating Explainable AI (XAI) into an AI-based IoT system. Using statistical theory (TRUST), they provided a XAI paradigm for numerical data, such as safety measures and information from networks for IoT, to provide transparency.

(Erik Cambria et.al, 2023) [7] have delved at XAI strategies that use natural language to express what has been done, what is occurring now, what are going to occur in the future, and supply the information on which these occurrences are based (via language or dialogue systems).They examined 70 XAI publications with natural language explanations that appeared between 2006 and 2021 in major journals and conferences. With the use of three distinct layers—definition of context, explanation construction, and message generation—they developed a framework for examining the whole learning process, from the black-box model to the final user. They also generated a list of each layer's attributes and contrasted it to the most common XAI literature methodologies.

(Kaveri A et.al, 2021)[8] Models using convolutional neural networks (CNNs) to find glaucoma in optical coherence tomography (OCT) pictures were generated and CNNs were assessed with thought sanctioning vectors (TCAVs) to identify which image concepts are used by CNNs to produce predictions. Researchers also compared the TCAV outcomes with the eye obsessions of specialists to identify regular dynamic features used by both artificial intelligence and human trained professionals.

(Jibhakate et. al, 2024) [9] Have talked about employing the VGG-16 and ResNet-50 machine learning models to diagnose glaucoma early. These two transfer learning algorithms were compared to one another. They looked into how convolutional network depth affected accuracy in big environments for picture recognition.

To aid in the diagnosis of glaucoma, (Civit-Masot et. al, 2021) [10] developed a system that analyses photographs of the inside of the eye (the fundus) using a trained and tested neural network. They used machine learning to locate both the optical disc and cup. They then transferred their expertise to a pre-trained CNN. To boost ultimate detection and discriminate glaucoma-positive cases, the outcomes of both approaches were combined.
An automated model for the diagnosis of retinal nerve fiber layer defects was proposed by (Panda et.al, 2022) [11]. Since it is an early example of glaucoma in fundus photos. The best approaches to stop eyesight loss are early identification and prevention. The novel technique uses an RNN driven by patch features to detect objects in fundus pictures. The dataset of fundus images is utilized to assess performance. High RNFLD detection and precise boundary localization are achieved by this approach.

A paper by (K.Choudhary et.al, 2021) [12] sought to use a cross-validation method to detect glaucoma in its early stages. To arrive at definitive proof, the authors analysed and computed symptoms that were present in individuals. Measures like blood pressure, age, sugar level, and myopia when pooled for different datasets were found to be associated with changes in glaucoma patients. The authors of this study analysed glaucoma disease using classification techniques including split validation and cross-validation algorithms. The conclusion shows that glaucoma can occur in persons with high blood pressure, high blood sugar, myopia, and a family history of the condition. Additionally, it has been noted that patients over 50 are more likely to develop glaucoma.

In this paper, (S. Jae Kim et.al, 2023) [13] investigated and attempted to create machine learning models with a strong predictive capacity and interpretability for the diagnosis of glaucoma based on RNFL thickness and visual field. Following the evaluation of the visual field and RNFL thickness, many features were gathered. The investigators created a glaucoma prediction model using four machine learning algorithms: C5.0, random forest, SVM, and K-nearest neighbor. Training datasets are used to build learning models, and validation datasets are used to assess how well the models perform. Ultimately, the authors noted that the random forest model performs the best and that the accuracy of the other models is comparable.

Fuzzy logic has also employed in [14] for the detection of glaucoma. The randomized Hough transform has been applied to feature selection and additional categorization. With this method, 96 percent accuracy has been attained.

The detection of the optic disk is a crucial step in the diagnosis of glaucoma. Authors in [15] have attempted with optic disk recognition and have composed about the challenges encountered in doing so because of changes in color intensity and blood vessel density. Any mistake in detection can result in an incorrect diagnosis.

DOMAIN OVERVIEW

Deep neural networks are now the state-of-the-art machine learning models across a variety of areas, from image analysis to natural language processing, and widely deployed in academia and industry. These developments have a huge potential for medical imaging technology, medical data analysis, medical diagnostics and healthcare in general, slowly being realized. We provide a short overview of recent advances and some associated challenges in machine learning applied to medical image processing and image analysis. Long before deep learning was used, traditional machine learning methods were mainly used. Such as Decision Trees, SVM, Naïve Bayes Classifier and Logistic Regression. These algorithms are also called flat algorithms. Flat here means that these algorithms cannot normally be applied directly to the raw data (such as .csv, images, text, etc.). We need a preprocessing step called Feature Extraction. The result of Feature Extraction is a representation of the given raw data that can now be used by these classic machine learning algorithms to perform a task. For example, the classification of the data into several categories or classes. Feature Extraction is usually quite complex and requires detailed knowledge of the problem domain. This preprocessing layer must be adapted, tested and refined over several iterations for optimal results. On the other side are the artificial neural networks of Deep

Learning. These do not need the Feature Extraction step. The layers are able to learn an implicit representation of the raw data directly and on their own. Here, a more and more abstract and compressed representation of the raw data is produced over several layers of artificial neural-nets. This compressed representation of the input data is then used to produce the result. The result can be, for example, the classification of the input data into different classes.

GLCM FEATURES

1. Contrast

Gray Level Co-occurrence Matrix (GLCM) features are crucial for analyzing medical images. GLCM

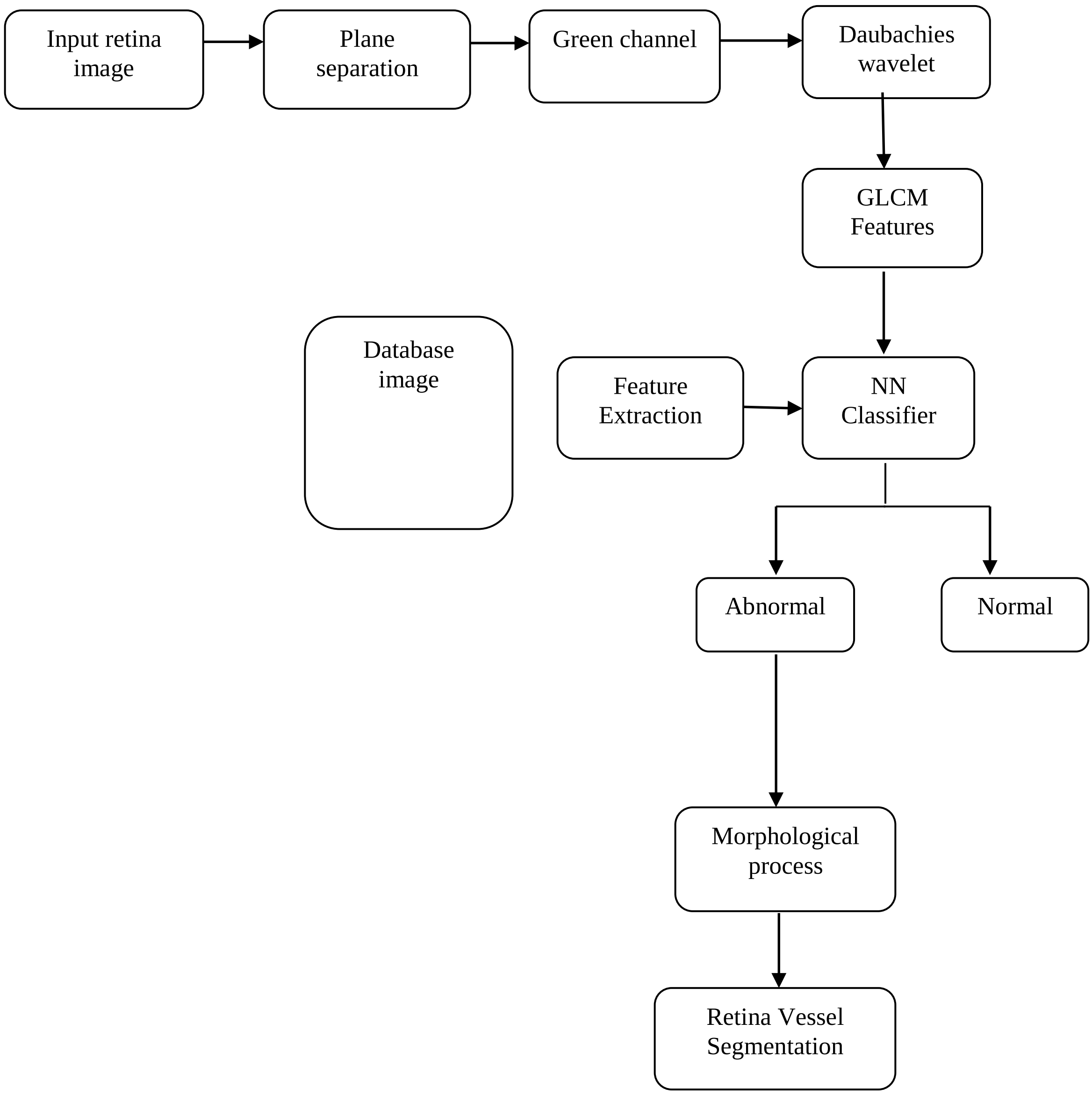
captures the spatial relationships of pixels in an image, allowing for the extraction of texture features that can help in various applications. Here are some key GLCM features and their relevance

- **Description**: Measures the intensity contrast between a pixel and its neighbor over the whole image.
- **Relevance**: Useful for distinguishing between healthy and diseased tissues, as disease often alters tissue texture.

2. Dissimilarity

- **Description**: Reflects the disparity between pixel values.
- **Relevance**: Helps in identifying boundaries and variations in tissues, aiding in tumor detection.

BLOCK DIAGRAM



3. Homogeneity

- **Description**: Measures the closeness of the distribution of elements in the GLCM to the GLCM diagonal.
- **Relevance**: High homogeneity indicates a more uniform texture, which can signify healthy tissue.

4. Energy

- **Description**: Represents the sum of squared elements in the GLCM.
- **Relevance**: High energy values indicate low variability in the image, often associated with healthy tissue.

5. Entropy

- **Description**: Measures the randomness in the pixel distribution.
- **Relevance**: Higher entropy can indicate more complex structures, often found in abnormal tissues.

6. Correlation

- **Description**: Measures the joint probability occurrence of the specified pixel pairs.
- **Relevance**: Helps assess the degree to which pixel values are correlated, aiding in identifying specific types of tissues.

Applications:

- **Tumor Detection**: GLCM features can differentiate between benign and malignant tumors by analyzing tissue texture.
- **Image Classification**: Used in machine learning algorithms for classifying images in radiology and pathology.
- **Disease Diagnosis**: Helps in the quantitative analysis of medical images, improving diagnostic accuracy.
- **Monitoring Disease Progression**: Changes in texture features over time can indicate disease progression or response to treatment.

WAVELET & GLCM FEATURES

Combining Wavelet Transform and Gray Level Co-occurrence Matrix (GLCM) features enhances texture analysis in biomedical imaging. Each method has distinct advantages that, when integrated, provide comprehensive insights into image characteristics. Here's a closer look at both methods and their combined application:

Wavelet Transform

Description: Wavelet Transform decomposes an image into different frequency components, allowing for multi-resolution analysis. It captures both spatial and frequency information, making it effective for analyzing textures at various scales.

Key Features:

1. **Energy**: The total energy of the wavelet coefficients can indicate the texture complexity.
2. **Entropy**: Measures the amount of information or randomness in the wavelet coefficients.
3. **Standard Deviation**: Indicates variability in texture, which can be crucial for differentiating between healthy and diseased tissue.
4. **Wavelet Variance**: Represents the spread of the wavelet coefficients, providing insights into texture roughness.

Gray Level Co-occurrence Matrix (GLCM)

Description: GLCM focuses on the spatial relationship of pixel values, capturing how often pairs of pixel with specific values occur in a specified spatial relationship.

Key Features:

- **Contrast**
- **Dissimilarity**
- **Homogeneity**
- **Energy**
- **Entropy**
- **Correlation**

Combined Approach

By integrating wavelet features with GLCM features, you can leverage the strengths of both methods. Here's how they complement each other:

1. **Multi-Resolution Analysis**: Wavelet Transform allows analysis at different scales, while GLCM captures local texture information. This combination provides a more nuanced understanding of texture.

2. **Improved Feature Discrimination**: The wavelet features can capture the overall structure of the image, while GLCM features can identify local patterns. Together, they can improve classification accuracy in applications like tumor detection.

3. **Robustness to Noise**: Wavelet Transform can help filter noise before computing GLCM features, resulting in more reliable texture analysis.

4. **Higher Dimensional Feature Space**: Combining features from both methods increases the dimensionality of the feature space, which can enhance machine learning models' ability to distinguish between classes.

Applications

1. **Tumor Classification**: Using both feature sets can improve the accuracy of distinguishing between benign and malignant tumors in medical images (e.g., MRI, CT scans).

2. **Texture Segmentation**: Helps in segmenting different tissue types in images, aiding in more precise diagnostic procedures.

3. **Disease Monitoring**: Changes in combined features over time can indicate disease progression or response to treatment.

TYPES OF WAVELET

Wavelets come in various types, each suited for different applications in signal processing and image analysis. Here are some of the most commonly used wavelet types:

1. Haar Wavelet

- **Description**: The simplest type of wavelet, which uses step functions.

- **Applications**: Useful for quick computations and simple image processing tasks, such as edge detection.

2. Daubechies Wavelet

- **Description**: A family of wavelets characterized by their compact support and smoothness. Named after Ingrid Daubechies.

- **Applications**: Widely used in image compression and denoising due to their ability to represent smooth signals effectively.

3. Symlet Wavelet

- **Description**: A modified version of Daubechies wavelets that are more symmetric.

- **Applications**: Preferred in applications where symmetry is crucial, such as in certain image processing tasks.

4. Coiflet Wavelet

- **Description**: Another variation of Daubechies wavelets that provides additional vanishing moments.

- **Applications**: Useful for applications requiring high precision, such as feature extraction in biomedical imaging.

5. Biorthogonal Wavelet

- **Description**: These wavelets allow for different analysis and synthesis wavelets, providing flexibility in applications.

- **Applications**: Commonly used in image compression (like JPEG 2000) and feature extraction.

6. Mexican Hat Wavelet (Ricker Wavelet)

- **Description**: A continuous wavelet resembling a Gaussian function but with a negative part.

- **Applications**: Often used in edge detection and identifying singularities in data.

7. Morlet Wavelet

- **Description**: A complex wavelet derived from a Gaussian modulated sine wave.

- **Applications**: Suitable for time-frequency analysis, particularly in analyzing oscillatory signals.

8. Continuous Wavelet Transform (CWT)

- **Description**: Utilizes a continuous range of scales and translations for analysis.

- **Applications**: Ideal for analyzing non-stationary signals, such as biomedical signals.

9. Discrete Wavelet Transform (DWT)

- **Description**: Involves discretely sampling scales and translations.

- **Applications**: Commonly used in image compression and feature extraction due to its computational efficiency.

PIXEL LEVEL IMAGE FUSION

Pixel-level image fusion is a technique used to combine multiple images of the same scene to create a single image that retains the most relevant information from each source. This approach is particularly useful in fields such as remote sensing, medical imaging, and surveillance. Here's an overview of pixel-level image fusion, its methods, advantages, and applications:

Key Concepts

1. **Objective**: To enhance the quality of images by integrating complementary information from different sources, improving the overall detail and feature representation.
2. **Input Types**: The images can vary in modality (e.g., visible, infrared, radar), resolution, or time of acquisition.

Common Methods of Pixel-Level Image Fusion

1. **Averaging**:
   - **Description**: Simply averages the pixel values of the input images.
   - **Pros**: Easy to implement; reduces noise.
   - **Cons**: Can blur fine details and may not highlight important features.
2. **Principal Component Analysis (PCA)**:
   - **Description**: Transforms the input images into a set of uncorrelated variables (principal components) and selects the most significant components for fusion.
   - **Pros**: Effective for dimensionality reduction and retaining variance.
   - **Cons**: Computationally intensive; may lose spatial information.
3. **Wavelet Transform**:
   - **Description**: Decomposes images into different frequency components. Fusing coefficients from different scales allows for detail preservation.
   - **Pros**: Captures both spatial and frequency information, useful for texture representation.
   - **Cons**: Requires careful selection of wavelet basis and fusion strategy.
4. **Histogram Equalization**:
   - **Description**: Adjusts the contrast of images based on their histograms before fusing.
   - **Pros**: Enhances visibility of features.
   - **Cons**: May lead to over-enhancement of noise.
5. **Multi-Resolution Analysis**:
   - **Description**: Combines images at different resolutions, often using wavelets or pyramids.
   - **Pros**: Preserves both global and local details.
   - **Cons**: More complex implementation.
6. **Intensity-Hue-Saturation (IHS) Transform**:
   - **Description**: Separates intensity from color information in RGB images for fusion.
   - **Pros**: Useful for integrating multispectral and panchromatic images.
   - **Cons**: May produce artifacts if not handled correctly.
7. **Deep Learning Techniques**:
   - **Description**: Uses neural networks to learn optimal fusion strategies from data.
   - **Pros**: Capable of capturing complex relationships in the data.
   - **Cons**: Requires substantial training data and computational resources.

Advantages of Pixel-Level Fusion

- **Enhanced Information**: Combines details from multiple images, improving overall image quality.
- **Feature Preservation**: Maintains important features such as edges, textures, and colors.
- **Noise Reduction**: Can help to mitigate the effects of noise present in individual images.

Applications

1. **Medical Imaging**: Combining MRI and CT scans to enhance diagnostic capabilities.
2. **Remote Sensing**: Merging multispectral and panchromatic images for improved land cover classification.
3. **Surveillance**: Integrating images from different sensors for better object detection and tracking.
4. **Photography**: Blending exposures to capture high dynamic range (HDR) images.

PLANE SEPARATION (GREEN CHANNEL SELECTION)

A Neural Network (NN) classifier is a type of machine learning model that uses the architecture and functioning of artificial neural networks to categorize input data into different classes. NN classifiers are widely used due to their ability to learn complex patterns in data. Here's an overview of key concepts, architecture, training, and applications:

Key Concepts

1. **Neurons**: The basic units of a neural network that process inputs, apply a weight, and pass the output through an activation function.
2. **Layers**:
   - **Input Layer**: The first layer that receives the input features.
   - **Hidden Layers**: Intermediate layers that learn to transform inputs into meaningful representations. There can be multiple hidden layers.
   - **Output Layer**: The final layer that produces the classification output.
3. **Activation Functions**: Functions applied to the output of each neuron, introducing non-linearity. Common activation functions include:
   - **Sigmoid**: Squashes output to (0, 1).
   - **ReLU (Rectified Linear Unit)**: Outputs the input directly if positive; otherwise, it outputs zero.
   - **Softmax**: Converts raw scores into probabilities for multi-class classification.
4. **Weights and Biases**: Parameters that are learned during training. Weights determine the strength of the connection between neurons, while biases provide additional flexibility.

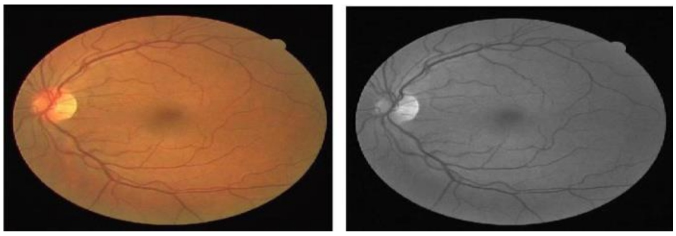
Architecture

A typical NN classifier consists of:

- **Input Layer**: Corresponding to the features of the input data.
- **Hidden Layers**: One or more layers where each neuron is connected to neurons in the previous and subsequent layers.
- **Output Layer**: One neuron for each class in the classification problem, with an activation function suitable for classification.

Training Process

1. **Forward Propagation**: Inputs are passed through the network layer by layer, producing an output.
2. **Loss Function**: A measure of how well the model's predictions match the actual labels. Common loss functions for classification include:
   - **Binary Cross-Entropy**: For binary classification.
   - **Categorical Cross-Entropy**: For multi-class classification.
3. **Backpropagation**: An algorithm used to update the weights and biases by calculating the gradient of the loss function with respect to each weight.
4. **Optimization**: Algorithms like Stochastic Gradient Descent (SGD), Adam, or RMSprop are used to minimize the loss function.



(a) Normal Retina image **(b) Green component extracted image**

Applications

1. **Image Classification**: Identifying objects in images (e.g., cats vs. dogs).
2. **Text Classification**: Categorizing documents, emails, or sentiments in reviews.
3. **Medical Diagnosis**: Classifying diseases based on medical imaging data or patient records.
4. **Speech Recognition**: Classifying spoken words or phrases.
5. **Fraud Detection**: Identifying fraudulent transactions in finance.

Advantages

- **Non-Linear Modeling**: Capable of modeling complex relationships in data.
- **Feature Learning**: Automatically learns features from raw data, reducing the need for manual feature extraction.
- **Scalability**: Can be scaled to handle large datasets and complex problems.

Disadvantages

- **Data Requirements**: Requires large amounts of labeled data for effective training.
- **Computationally Intensive**: Training can be resource-intensive and time-consuming.
- **Overfitting**: Can memorize training data, leading to poor generalization on unseen data if not properly regularized.

DISCRETE WAVELET TRABSFORM

The Discrete Wavelet Transform (DWT) is a mathematical technique used in signal processing and image analysis to decompose signals into their constituent parts at various frequency levels. It is particularly valuable for tasks such as image compression, feature extraction, and denoising. Here's an overview of DWT, its principles, applications, and advantages:

Key Concepts

1. **Wavelets**:
   - Wavelets are small waves that are localized in both time (and space) and frequency. They allow for multi-resolution analysis of signals.
2. **Multi-Resolution Analysis**:
   - DWT enables analysis of a signal at different resolutions, allowing for the examination of both coarse and fine details.
3. **Filters**:
   - DWT uses pairs of filters (low-pass and high-pass) to analyze the signal:
     - **Low-Pass Filter**: Captures the approximation coefficients (low-frequency components).
     - **High-Pass Filter**: Captures the detail coefficients (high-frequency components).

DWT Process

1. **Decomposition**:
   - The original signal (or image) is passed through the low-pass and high-pass filters.
   - The results are then down sampled (reducing the number of samples by half) to produce the approximation and detail coefficients.
2. **Recursive Application**:
   - This process can be repeated on the approximation coefficients to further decompose the signal into multiple levels. For an image, this results in four sets of coefficients at each level: approximation (LL), horizontal detail (LH), vertical detail (HL), and diagonal detail (HH).

Applications

1. **Image Compression**:
   - DWT is widely used in image compression techniques, such as JPEG 2000. It allows for efficient representation of images by focusing on significant features while reducing redundancy.
2. **Feature Extraction**:
   - In applications like image classification and object detection, DWT can be used to extract meaningful features based on texture and shape.
3. **Denoising**:
   - DWT can help remove noise from signals or images by thresholding the detail coefficients, allowing for cleaner reconstructions.
4. **Signal Processing**:
   - Used in various fields for analyzing time-varying signals, including biomedical signals, audio signals, and more.

Advantages

- **Time-Frequency Localization**: DWT provides a time-frequency representation of signals, making it easier to analyze non-stationary signals.
- **Computational Efficiency**: DWT is computationally more efficient than other transforms like the Fourier Transform, especially for large datasets.
- **Robustness**: Offers good performance in terms of noise resistance and the ability to handle various signal types.

CNN classifier

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3. **Backpropagation**: An algorithm used to update the weights and biases by calculating the gradient of the loss function with respect to each weight.
4. **Optimization**: Algorithms like Stochastic Gradient Descent (SGD), Adam, or RMSprop are used to minimize the loss function.

Applications

1. **Image Classification**: Identifying objects in images (e.g., cats vs. dogs).
2. **Text Classification**: Categorizing documents, emails, or sentiments in reviews.
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- **Computationally Intensive**: Training can be resource-intensive and time-consuming.
- **Overfitting**: Can memorize training data, leading to poor generalization on unseen data if not properly regularized.

MORPHOLOGICAL PROCESS

Morphological processing is a technique in image analysis that focuses on the structure and shape of objects within an image. It is widely used in computer vision and image processing for tasks such as segmentation, feature extraction, and object detection. Here’s an overview of key concepts, operations, and applications of morphological processing:

Key Concepts

1. **Structuring Element**:

   A small, predefined shape (e.g., a square, circle, or line) used to probe the image. The choice of structuring element determines the nature of the morphological operation.

2. **Binary vs. Grayscale Morphology**:

   Binary Morphology: Works with binary images (black and white) where pixels are either 0 or 1.

   Grayscale Morphology: Operates on grayscale images, allowing for more complex analysis by considering pixel intensity values.

Basic Morphological Operations

1. **Dilation**:

Description: Expands the boundaries of objects in a binary image.

Effect: Adds pixels to the object boundaries, making objects larger.

Use Case: Useful for closing small gaps and connecting disjointed parts of an object.

2. **Erosion**:

Description: Shrinks the boundaries of objects in a binary image.

Effect: Removes pixels from the object boundaries.

Use Case: Useful for removing small noise points or separating connected objects.

3. **Opening**:

Description: Performs erosion followed by dilation.

Effect: Removes small objects or noise while preserving the shape and size of larger objects.

Use Case: Useful for smoothing object boundaries.

4. **Closing**:

Description: Performs dilation followed by erosion.

Effect: Fills small holes and gaps in objects while preserving their overall shape.

Use Case: Useful for connecting disjoint parts of an object.

5. **Morphological Gradient**:

Description: The difference between dilation and erosion of an image.

Effect: Highlights edges by emphasizing the boundaries of objects.

Use Case: Useful for edge detection.

6. **Hit-or-Miss Transform**:

Description: Detects specific shapes within a binary image.

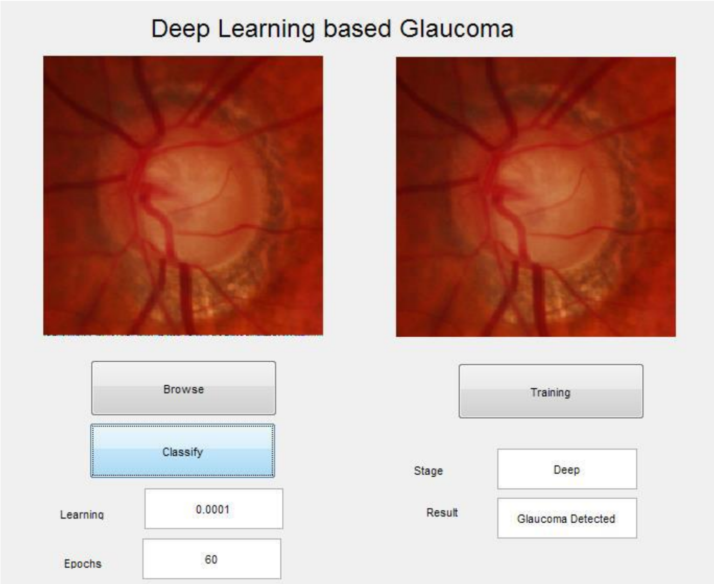
Effect: Combines dilation and erosion to identify patterns that match the structuring element.

Use Case: Useful for template matching and shape recognition.

Applications

1. **Image Segmentation**: Morphological operations help separate objects from the background or from each other.
2. **Noise Reduction**: Opening and closing operations are effective in removing small noise while preserving important structures.
3. **Feature Extraction**: Helps in identifying and extracting relevant shapes or features from an image.
4. **Object Recognition**: Morphological features can assist in recognizing and classifying objects based on their shape and structure.
5. **Medical Imaging**: Used for analyzing structures in medical images, such as identifying tumors or blood vessels.
6. **Document Image Analysis**: Helps in recognizing characters and structures in scanned documents.

RESULT ANALYSIS



COMPARISON

(Borwankar et.al, 2022) Submitted a study where uses of two datasets, DRISHTI and REFUGEE, which may not be comprehensive enough to cover all variations of glaucoma cases. The model's ability to generalize to different populations and diverse image qualities is not thoroughly tested. While the paper compares its results with previous approaches, it does not extensively explore other potential deep learning architectures. Adding the practical implementation and usability of the proposed system in real-world clinical settings are not discussed in detail.[33]

(Juneja et.al, 2020) have proposed a work on Glaucoma is a leading cause of irreversible blindness, characterized by increased intraocular pressure damaging the optic nerve. The paper proposes a deep learning model, G-net, which uses convolutional neural networks (CNNs) to segment the optic disc and optic cup from fundus images. In this Paper the model achieved an accuracy of 95.8% for optic disc segmentation and 93% for optic cup segmentation. The model was tested on the DRISHTI-GS dataset, which includes 101 images from Aravind Eye Hospital, Madurai, India. Further research is needed to test the system in real-world clinical settings to evaluate its practical utility and effectiveness. More comparative studies with other existing methods are required to establish the superiority or advantages of the proposed approach. [34]

(Serte et.al, 2019) was the study that author was suggested a generalized deep learning model for detecting glaucoma using fundus images, trained and tested on multiple datasets and architectures .The methodology Utilizes ResNet-50, ResNet-152, and GoogLeNet architectures, trained on four datasets and tested on a fifth to ensure robustness. The model shows comparable or better performance than previous works 80% of the time, particularly excelling in specificity. In this article author used Five public datasets are used: HRF, Drishti-GS1, RIM-ONE, sjchoi86-HRF, and ACRIMA5 where as our article provides more practical insights in healthcare sector. [35]

(Saxena et.al, 2020) Submitted a study where it aims to develop a deep learning model using CNN to detect glaucoma, a disease that can lead to irreversible vision loss. Here the proposed model uses a six-layer CNN architecture with dropout mechanisms to improve performance1. It analyzes images from the SCES and ORIGA datasets where the model achieved AUC values of 0.822 for the ORIGA dataset and 0.882 for the SCES dataset, indicating high accuracy in detecting glaucoma. In our work we focus on adding other biometrics and health data which can improve authentication accuracy even better.

CONCLUSION

This article presented detailed investigation of various glaucoma detection methods. Early diagnosis of glaucoma is essential as it is among the most dangerous eye conditions that can asymptomatically result in sightlessness, is necessary to help patients avoid total loss of vision. Deep learning models have been shown to be helpful for facilitating this early diagnosis. In this study, various methods for diagnosing glaucoma are examined and mean accuracy, specificity, and sensitivity are considered. Glaucoma is a chronic, irreversible eye condition that affects people worldwide and can cause blindness. This process has to be automated, and a reliable and efficient computer-aided diagnosis tool for glaucoma diagnosis has to be created. In this work, we have introduced an affordable digital system that can diagnose glaucoma more accurately than prior techniques. The suggested system, which consists of ResNet, performs rather well in comparison to an ophthalmologist, allowing for quicker and less expensive patient care. This algorithm attains the accuracy of 98.9% and F1 score of 98.8% on the classification of glaucoma infected eye sample. This test result is more accurate than earlier CNN approaches that were used.By utilizing deep learning for image classification, the project aims to improve diagnostic accuracy and efficiency in glaucoma detection, potentially reducing the burden of this preventable cause of blindness.

References

[1] Chen, H. S. L., Chen, G. A., Syu, J. Y., Chuang, L. H., Su, W. W., Wu, W. C., ... & Kang, E. Y. C. (2022). Early Glaucoma Detection by Using Style Transfer to Predict Retinal Nerve Fiber Layer Thickness Distribution on the Fundus Photograph. Ophthalmology Science, 2(3), 100180.

[2] Diaz-Pinto, A., Morales, S., Naranjo, V., Köhler, T., Mossi, J. M., & Navea, A. (2019). CNNs for automatic glaucoma assessment using fundus images: an extensive validation. Biomedical engineering online, 18(1), 1-19.

[3] M. Juneja, S. Singh, N. Agarwal et al., "Automated detection of Glaucoma using deep learning convolution

network (G-net)". Multimed Tools Appl 79, 15531–15553, 2020.

[4] Liao, W., Zou, B., Zhao, R., Chen, Y., He, Z., & Zhou, M. (2019). Clinical interpretable deep learning model for glaucoma diagnosis. IEEE journal of biomedical and health informatics, 24(5), 1405-1412.

[5] Kim, M., Janssens, O., Park, H. M., Zuallaert, J., Van Hoecke, S., & De Neve, W. (2018). Web applicable computer-aided diagnosis of glaucoma using deep learning. arXiv preprint arXiv:1812.02405.

[6] Prabhakar, B., Singh, R. K., & Yadav, K. S. (2021). Artificial intelligence (AI) impacting diagnosis of glaucoma and understanding the regulatory aspects of AI-based software as medical device. Computerized Medical Imaging and Graphics, 87, 101818.

[7] Jun, T. J., Eom, Y., Kim, D., Kim, C., Park, J. H., Nguyen, H. M., ... & Kim, D. (2021). TRk-CNN: transferable ranking-CNN for image classification of glaucoma, glaucoma suspect, and normal eyes. Expert Systems with Applications, 182, 115211.

[8] Wu, Y., Szymanska, M., Hu, Y., Fazal, M. I., Jiang, N., Yetisen, A. K., & Cordeiro, M. F. (2022). Measures of disease activity in glaucoma. Biosensors and Bioelectronics, 196, 113700.

[9] Xue, Y., Zhu, J., Huang, X., Xu, X., Li, X., Zheng, Y., ... & Si, K. (2022). A multi-feature deep learning system to enhance glaucoma severity diagnosis with high accuracy and fast speed. Journal of Biomedical Informatics, 136, 104233.

[10] Bisneto, T. R. V., de Carvalho Filho, A. O., & Magalhães, D. M. V. (2020). Generative adversarial network and texture features applied to automatic glaucoma detection. Applied Soft Computing, 90, 106165.

[11] Parashar, D., & Agrawal, D. K. (2020). Automated classification of glaucoma stages using flexible analytic wavelet transform from retinal fundus images. IEEE Sensors Journal, 20(21), 12885-12894.

[12] George, Y., Antony, B. J., Ishikawa, H., Wollstein, G., Schuman, J. S., & Garnavi, R. (2020). Attention-guided 3D-CNN framework for glaucoma detection and structural-functional association using volumetric images. IEEE Journal of Biomedical and Health Informatics, 24(12), 3421-3430.

[13] Shamia, D., Prince, S., & Bini, D. (2022, April). An Online Platform for Early Eye Disease Detection using Deep Convolutional Neural Networks. In 2022 6th International Conference on Devices, Circuits and Systems (ICDCS) (pp. 388-392). IEEE.

[14] An, G., Omodaka, K., Tsuda, S., Shiga, Y., Takada, N., Kikawa, T., ... & Akiba, M. (2018). Comparison of machine-learning classification models for glaucoma management. Journal of healthcare engineering, 2018.

[15] Kamal, M. S., Dey, N., Chowdhury, L., Hasan, S. I., & Santosh, K. C. (2022). Explainable AI for glaucoma prediction analysis to understand risk factors in treatment planning. IEEE Transactions on Instrumentation and Measurement, 71, 1-9.

[16] Priyanka, V., and V. Uma Maheswari. "Automated Glaucoma Detection Using Cup to Disk Ratio and Grey Level Co-occurrence Matrix." In Machine Learning and Information Processing: Proceedings of ICMLIP 2020, pp. 425-434. Springer Singapore, 2021.

[17] Siddiqui, K., & Doyle, T. E. (2022, September). Trust Metrics for Medical Deep Learning Using Explainable-AI Ensemble for Time Series Classification. In 2022 IEEE Canadian Conference on Electrical and Computer Engineering (CCECE) (pp. 370-377). IEEE.

[18] Carrieri, A. P., Haiminen, N., Maudsley-Barton, S., Gardiner, L. J., Murphy, B., Mayes, A. E.,& Pyzer-Knapp, E. O. (2021). Explainable AI reveals changes in skin microbiome composition linked to phenotypic differences. Scientific reports, 11(1), 1-18.

[19] Fujita, K., Shibahara, T., Chiba, D., Akiyama, M., & Uchida, M. (2022, May). Objection!: Identifying Misclassified Malicious Activities with XAI. In ICC 2022-IEEE International Conference on Communications (pp. 2065-2070). IEEE.

[20] Abeyagunasekera, S. H. P., Perera, Y., Chamara, K., Kaushalya, U., Sumathipala, P., & Senaweera, O. (2022, April). LISA: Enhance the explainability of medical images unifying current XAI techniques. In 2022 IEEE 7th International conference for Convergence in Technology (I2CT) (pp. 1-9). IEEE.

[21] Murray, B., Anderson, D. T., & Havens, T. C. (2021, July). Actionable XAI for the Fuzzy Integral. In 2021 IEEE International Conference on Fuzzy Systems (FUZZ-IEEE) (pp. 1-8). IEEE.

[22] Cambria, E., Malandri, L., Mercorio, F., Mezzanzanica, M., & Nobani, N. (2023). A survey on XAI and natural language explanations. Information Processing & Management, 60(1), 103111.

[23] Fu, H., Cheng, J., Xu, Y., Wong, D. W. K., Liu, J., & Cao, X. (2018). Joint optic disc and cup segmentation based on multi-label deep network and polar transformation. IEEE transactions on medical imaging, 37(7), 1597-1605.

[24] Pinos-Velez, E., Flores-Rivera, M., Ipanque-Alama, W., Herrera-Alvarez, D., Chacon, C., & Serpa-Andrade, L. (2018, October). Implementation of support tools for the presumptive diagnosis of Glaucoma through identification and processing of medical images of the human eye. In 2018

IEEE International Systems Engineering Symposium (ISSE) (pp. 1-5). IEEE.

[25] Vaghjiani, D., Saha, S., Connan, Y., Frost, S., & Kanagasingam, Y. (2020, November). Visualizing and understanding inherent image features in CNN-based glaucoma detection. In 2020 Digital Image Computing: Techniques and Applications (DICTA) (pp. 1-3). IEEE.

[26] Diaz-Pinto, A., Colomer, A., Naranjo, V., Morales, S., Xu, Y., & Frangi, A. F. (2019). Retinal image synthesis and semi-supervised learning for glaucoma assessment. IEEE transactions on medical imaging, 38(9), 2211-2218.

[27] Sarhan, M. H., Nasseri, M. A., Zapp, D., Maier, M., Lohmann, C. P., Navab, N., & Eslami, A. (2020). Machine learning techniques for ophthalmic data processing: a review. IEEE Journal of Biomedical and Health Informatics, 24(12), 3338-3350.

[28] Manassakorn, A., Auethavekiat, S., Sa-Ing, V., Chansangpetch, S., Ratanawongphaibul, K., Uramphorn, N., & Tantisevi, V. (2022). GlauNet: Glaucoma Diagnosis for OCTA Imaging Using a New CNN Architecture. IEEE Access, 10, 95613-95622.

[29] Carrillo, J., Bautista, L., Villamizar, J., Rueda, J., & Sanchez, M. (2019, April). Glaucoma detection using fundus images of the eye. In 2019 XXII Symposium on Image, Signal Processing and Artificial Vision (STSIVA) (pp. 1-4). IEEE.

[30] Lavric, A., Petrariu, A. I., Havriliuc, S., & Coca, E. (2021, November). Glaucoma Detection by Artificial Intelligence: GlauNet A Deep Learning Framework. In 2021 International Conference on e-Health and Bioengineering (EHB) (pp. 1-4). IEEE.

[31] Ramanathan, G., Chakrabarti, D., Patil, A., Rishipathak, S., & Kharche, S. (2021, October). Eye Disease Detection Using Machine Learning. In 2021 2nd Global Conference for Advancement in Technology (GCAT) (pp. 1-5). IEEE.

[32] Jibhakate, P., Gole, S., Yeskar, P., Rangwani, N., Vyas, A., & Dhote, K. (2022, July). Early Glaucoma Detection Using Machine Learning Algorithms of VGG-16 and Resnet-50. In 2022 IEEE Region 10 Symposium (TENSYMP) (pp. 1-5). IEEE.

[33] Borwankar, S., Sen, R., & Kakani, B. (2020, July). Improved glaucoma diagnosis using deep learning. In 2020 IEEE International conference on electronics, computing and communication technologies (CONECCT) (pp. 1-4). IEEE.

[34] Juneja, M., Singh, S., Agarwal, N., Bali, S., Gupta, S., Thakur, N., & Jindal, P. (2020). Automated detection of Glaucoma using deep learning convolution network (G-net). Multimedia Tools and Applications, 79, 15531-15553.

[35] Serte, S., & Serener, A. (2019, October). A generalized deep learning model for glaucoma detection. In 2019 3rd International symposium on multidisciplinary studies and innovative technologies (ISMSIT) (pp. 1-5). IEEE.

[36] Saxena, A., Vyas, A., Parashar, L., & Singh, U. (2020, July). A glaucoma detection using convolutional neural network. In 2020 international conference on electronics and sustainable communication systems (ICESC) (pp. 815-820). IEEE.