

Automated Glaucoma Detection In Retinal Fundus Images Using Deep Learning And Hybrid Feature Models

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Abstract:

- Glaucoma is an eye disease that gets worse over time and can ruin your sight if it is not found early. Expert analysis is needed for traditional diagnostic methods, which can be subjective and take a lot of time. This study uses two standard datasets, ACRIMA and ORIGA, to test how deep learning techniques can be used to find glaucoma on its own. Within this study, deep learning models such as ResNet50, DenseNet, and Vgg16 are utilized to extract features and organize photos of individuals with and without glaucoma. Different views of the eyes can be found in the ORIGA dataset and the ACRIMA dataset. That way, they can see how well they teach machine learning models. At 84% of the times it was tried, DenseNet121 with SVM (RBF) was the most accurate model. With 81%, ResNet50 with SVM (RBF) came in second, and VGG16 with Random Forest got 80%. Each of these types worked well and did a good job. Tests show that models learned on ACRIMA are more sensitive, while models learned on ORIGA are more general because of its variety. Combining traits from both datasets improves classification performance, which suggests that a strong glaucoma detection system might be possible. This study shows how important diverse datasets and advances in machine learning are for finding glaucoma earlier and helping eye doctors treat and intervene in time.

Keywords: - Machine Learning, Deep learning, Glaucoma, Logistic Regression, Random Forest, Vgg16, Resnet50, MobileNet.

I. Introduction

Once you have glaucoma, it gets worse over time and can leave you blind for life if it is not treated. One of the main reasons people lose their sight, it affects millions of people around the world particularly the elderly. The disease primarily damages the optic nerve, often due to increased intraocular pressure (IOP). Since glaucoma develops gradually and remains asymptomatic in its early stages, many individuals remain unaware of their condition until significant vision impairment occurs. Early detection is crucial for effective disease management, as timely intervention can slow its progression and prevent blindness.

Traditional glaucoma diagnosis relies on clinical examinations such as intraocular pressure measurement, visual field tests, and optical coherence tomography (OCT). While these methods are widely used, they suffer from several limitations, including dependence on specialized equipment, variability in expert interpretation, and the inability to detect the disease at an early stage. Furthermore, manual diagnosis is time-consuming and subject to human error, making it hard to set up large-scale screening programs, especially in places where eye doctors are hard to find.

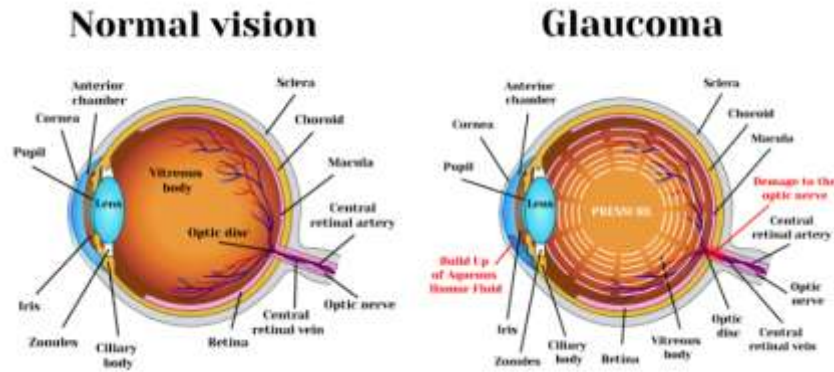


Fig 1: Glaucoma disease

Fig 1 shows normal vision and glaucoma disease. Recent advancements in machine learning (ML) and deep learning have introduced automated and highly accurate approaches for medical image analysis. These techniques can analyze retinal fundus images, extract essential features, and classify images into glaucomatous and non-glaucomatous categories with minimal human intervention. This study explores the application of ML-based models for glaucoma diagnosis using two benchmark datasets, ACRIMA and ORIGA. By comparing the effectiveness of these datasets in training machine learning models, we aim to enhance diagnostic accuracy and propose a robust, scalable solution for early glaucoma detection. Our findings contribute to the growing field of AI-driven ophthalmology and highlight the potential of ML in improving clinical decision-making.

Overview of glaucoma

Glaucoma is a key reason for eyesight loss in people above 60. In contrast to vision formation, this disease damages the optic nerve. One alarming issue is that only approximately 50% of individuals with glaucoma are aware of their condition. Fig. 2 shows the difference between a healthy eye and one with glaucoma induced by intraocular pressure and visual deficit. Loss of peripheral vision is among the chief symptoms of glaucoma. However, that does not mean peripheral vision is always the first to be lost. Sometimes, especially seen in normal-tension glaucoma, the initial loss is in paracentral vision, that is, in areas a little off-center from the actual line of sight. Glaucoma adversely affects the optic nerve head (ONH), which relays sensory information from the eye to the brain. Vision loss can be delayed with therapeutic measures, but already lost vision cannot be restored.

Figure 5 displays a retinal fundus picture of both a healthy eye and an eye with glaucoma that was studied. An Optic Disc (OD), Optic Cup (OC), and blood vessels along with the retina are all included in a retinal fundus scan. The OD describes the round area in the back of the eye where the optic nerve head (ONH) meets the retina. Within the Retina, the OC is located within the OD; it is the brightest spot in the middle. It is made up of the neuroretinal rim, which can be thin or thick depending on the shape of the OD [38]. The OD and OC's position, form, size, and color, as well as the blood vessels right next to the optic nerve, can help doctors diagnose glaucoma.

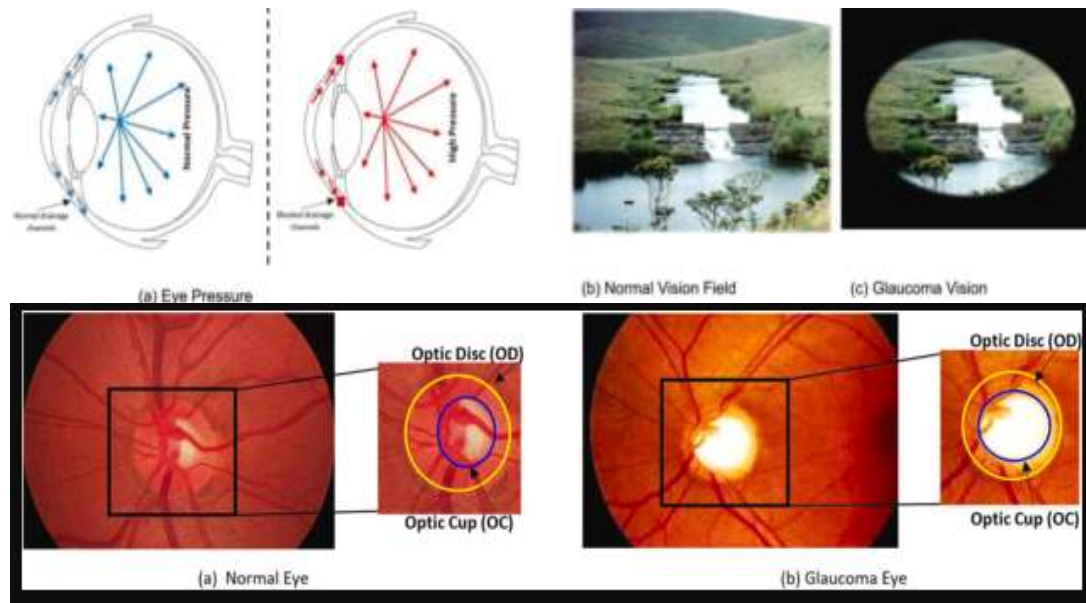


Fig 2. Healthy eye vs glaucoma eye.[38]

ACRIMA and ORIGA Datasets: Overview and Details

The ACRIMA and ORIGA datasets, possessing high-resolution images, have been used in machine learning research for glaucoma detection in developing and evaluating automated diagnostic models. These datasets support the enhancement of early detection methods by providing good-quality labeled images that can be analyzed using deep learning.

ACRIMA Dataset

The ACRIMA dataset consists of 705 retinal fundus images collected from clinical and ophthalmology departments. Among them, 396 images have been labeled as glaucomatous, whereas 309 of those are labeled as non-glaucomatous. This dataset is fairly distributed and contains high-resolution retinal images, very much suitable for deep learning classification models. It provides detailed images of the optic nerve head (ONH), which is essential for finding abnormalities related to glaucoma. The main advantage of the ACRIMA dataset is in fundus image classification by machine learning algorithms in order to characterize healthy and glaucomatous eyes.

ORIGA Dataset (Optic Disc and Rim Ground Truth Dataset)

ORIGA, being a large-scale public dataset, is mainly used for optic disc and cup segmentation, which is critical toward glaucoma detection. It consists of 650 retinal images collected from the Singapore Malay Eye Study (SiMES), with expert annotation of the optic disc and cup regions. Of these, around 168 images are labeled glaucomatous whereas the rest are labeled non-glaucomatous. It provides the ground truth segmentation of optic disc and cup boundaries in detail, thus possessing great importance for development and evaluation of glaucoma detection models based on segmentation. Because these images are sourced from a variety of real-world clinical environments, the diversity in the dataset ameliorates generalization among machine learning models in varying imaging settings.

Table 1: Comparison of ACRIMA and ORIGA Dataset

Feature	ACRIMA Dataset	ORIGA Dataset
Number of Images	705	650

Glaucoma Cases	396	168
Image Type	Retinal Fundus Images	Retinal Fundus Images
Annotations	Binary classification (Glaucomatous/Healthy)	Optic Disc & Cup segmentation with glaucoma labels
Source	Clinical ophthalmology departments	Singapore Malay Eye Study (SiMES)
Best Use Case	Classification-based glaucoma detection	Segmentation-based analysis for optic disc and cup detection

Both ACRIMA and ORIGA datasets play a critical role in advancing glaucoma detection using machine learning. ACRIMA is more suited for classification-based models, while ORIGA is ideal for segmentation-based approaches. Utilizing both datasets together can enhance the robustness of automated glaucoma screening systems, improving accuracy and early detection capabilities.

II. Literature Review

Wan et al.[1] reviews recent datasets, diagnostic methods, and AI algorithms applied to DED detection. It categorizes DED diagnostic approaches into three groups based on their use of AI: those with established standards, AI-enhanced methods, and supplementary approaches. The study recommends standardized DED detection protocols, integrating multiple diagnostic criteria, and outlines future research directions. Overall, it highlights AI's potential to advance ophthalmic disease detection, bridging academic insights with practical applications in ophthalmology.

Luo et al.[2] improve fairness in medical imaging by addressing disparities among racial and ethnic groups. It introduces fair identity normalization (FIN) to mitigate biases in machine learning models, crucial for equitable healthcare diagnostics. Their equity-scaled performance measure offers a standardized way to assess fairness across diverse demographic groups, setting a benchmark for future research in healthcare-focused fairness learning.

Albelaihi et al.[3] proposed a multi-classification deep learning model meant to diagnose four diabetic eye diseases (DR, DME, Glaucoma, and Cataract) on 1228 images from 6 datasets: DIARETDB0, DIARETDB1, Messidor, HEI-MED, Ocular, and Retina. The evaluations used two types of geometric augmentation, i.e., online patching and offline patching methods, and compared five different types of architecture, i.e., EfficientNetB0, VGG16, ResNet152V2, ResNet152V2+GRU, and ResNet152V2+Bi-GRU. EfficientNetB0 performed best, with accuracy, recall, and precision of 98.76%, making palpable improvements over previous work like Fast-RCNN, RCNN-LSTM, and InceptionResNet in accuracy, recall, precision, and AUC.

Kalita et al.[4] Glaucoma, a significant global health concern recognized by the WHO, progresses via optic nerve damage from increased eye pressure, leading to blindness. Early detection through regular eye exams is critical, as glaucoma often lacks symptoms in early stages. Advanced feature engineering in machine learning uncovers biomarkers crucial for early diagnosis and enhances automated ophthalmology systems.

The method increases the size of the ocular cup while maintaining the size of the ocular disk [5] fundus image and CDR technique to detect glaucoma, an unusual eye condition affecting adults over 40, young adults, children, and infants, but can sometimes result from eye surgery. [6] for diagnosing glaucoma using CDR evaluation of preprocessed

fundus images, comparing their accuracy based on sensitivity and specificity[7] introduces an automatic image processing method for glaucoma diagnosis from digital fundus images, achieving a 94.7% accuracy rate compared to existing methods [8] discusses the use of image processing techniques for automatic detection of glaucoma, a neurodegenerative eye disease, including registration, fusion, segmentation, feature extraction, and statistical measurements [9] proposes a new method for detecting glaucoma disease by analyzing retinal nerve fiber layer damage. The method involves two stages: pre-treatment and classification. The method, evaluated on the ORIGA dataset, achieved an accuracy of 92.88% with an AUC of 89.34%, a 15% improvement from previous research. [10] learning-based method for automatic segmentation of optic discs and optic cups, with a detection rate of 96.75% for glaucoma, based on DRIVE and DIARETDB1 image datasets.[11] Describes a new way to automatically find glaucoma using stereo pair fundus images. The optic cup-to-disc area ratio is used to achieve 86% accuracy. Deep learning (DL) methods were used in [12] to help with glaucoma mass screening, lower the cost, and make it possible to reach more people. Both OD and OC dice segments exceeded 0.8, and IoU segments exceeded 0.7. It has a sensitivity of 0.8, a specificity of 0.7, an F1-Score of about 0.7, and an AUC high above 0.85. [13] advanced segmentation technique and dynamic ensemble selection classifier outperform deep learning-based U-Net in classifying glaucoma, with a higher mean accuracy of 0.96.[14] A hierarchical and deep learning system was proposed to replicate the diagnostic thinking of the human expert, with intermediate processes made transparent and interpretable. The prewise [15] to limnologists in determining the severity of glaucoma from cup-to-disc ratio values. It involves preprocessing, segmentation, feature extraction, and classification into early, moderate, and advanced glaucoma. The system was tested on 40 data points and obtained an accuracy rate of, 95%, 93.91% precision, recall of 91.37%, and a specificity of 95.86%.[16] Glaucoma disease classification with a perceptron-type convolutional multi-layer neural network scrutinizing accuracy, sensitivity, specificity, and Jaccard parameters for the segmentation of OC (optic cup) and OD (optic disc).[17] proposes an offline CAD system for diagnosis of glaucoma using retinal fundus images. Image validation of 99% Le-Net. A 98.67% success rate was reached for ROI extraction with the help of the brightest spot method. Also, the U-Net design had a dice coefficient of 0.93 for the optic disc and 0.87 for the optic cup.[18] A hybrid set derived from structural and nonstructural features for classifying retinal fundus images that may be used as a second opinion for ophthalmologists bunches (FoS), Higher Order Spectra (HOS), Higher Order Cumulant (HOC), and Wavelets.

Table 1: Comparative Glaucoma Detection with ACRIMA & ORIGA

Ref	Technique Used	Datasets Used	Results / Metrics	Limitations	Key Findings
[28]	ViT + Bi-GRU on 3D OCT volumes	OCT (volumetric; no ACRIMA/ORIGA)	F1 93.6%, MCC 73.5%, AUC 95.2%	Not fundus-based; no ACRIMA/ORIGA	Captures spatial and slice-wise features in volumetric data
[29]	CNN + ViT hybrid + Cross-Attention + Grad-CAM	ACRIMA, Drishti	Qualitative explainability ; metrics pending	Preprint; no quantitative results yet	Offers interpretable glaucoma screening using

					attention maps
[30]	U-Net + EfficientNet-B0; ROI + augmentation	ORIGA, RIM-ONE DL, HRF	Best AUC: high (~99%) across ORIGA/RIM-ONE/HRF	No ACRIMA; some overfitting with large batches	ROI segmentation + augmentation improves AUC significantly
[31]	Capsule network (Xception + MIV-C2)	ACRIMA, RIM-ONE v2	ACRIMA Acc 98.2%, AUC 97.3%	Only two datasets; ORIGA not included	Capsule NN excels in small dataset scenarios
[32]	DenseNet-121 + CBAM attention	ACRIMA, RIM-ONE	Improved metrics vs baseline	No ORIGA used	Dual attention enhances feature focus and accuracy
[33]	G-RISK regression (CNN)	ACRIMA, ORIGA, REFUGE, BMES, GHS etc.	AUC 0.854–0.988 across datasets; high sensitivity	Needs prospective validation	Demonstrates excellent generalizability across diverse data
[34]	Ensemble regression over multiple CNNs	ACRIMA ORIGA + 10+ others	Acc 0.95, Prec 0.98, Rec 0.87 on ORIGA/ACRIMA	Minimal clinical deployment info	High performance and consistency across datasets
[35]	Systematic review of CNN strategies	ACRIMA, ORIGA, REFUGE etc.	No novel metrics; survey style	Review—no new model	Highlights the importance of segmentation and interpretability
[36]	ResNet-50 on grayscale augmented fundus	ORIGA, RIM-ONE, DRISHTI-GS, G1020	Acc 98.48%, Sens 99.3%, Spec 96.5%, AUC 97% (G1020)	Several datasets; limited ORIGA-specific metrics	High performance with grayscale-channel fusion
[37]	Optimization-based feature + ELM classifier	ACRIMA, ORIGA, RIM-ONE	Acc 96.8%–93.2% across datasets; sens/spec ~92–96%	Shallow features vs deep nets; need CNN comparison	Efficient feature-based model with explainable heatmaps

III. Proposed Methodology

Methodology

The proposed methodology for glaucoma disease classification using deep learning begins with defining the research objective and understanding the challenges in glaucoma detection. To begin, the need to load Datasets 1 and 2, which contain labeled shots of the retina. In these files, the data is checked for quality and correctness before it is used. Next, feature extraction is used to find important things like the ONH structure, the CDR, and the RNF width. Highly advanced image editing techniques are used to make details stand out more. Increasing contrast, lowering noise, and normalizing the picture are a few examples. If you want to make sure the evaluation process is fair, the dataset is split into 80% training and 20% testing after the features are removed. The class distribution is kept pure by using stratified sampling. To identify glaucoma, the next step is to make deep learning models. Various approaches are considered for model training, including Transformer-based models and Convolutional Neural Networks (CNNs) such as ResNet, VGG16, and VGG19. A variety of hyperparameter optimization techniques are used to boost model performance. These include changing batch sizes, learning rate tuning, and dropout regularization. Furthermore, transfer learning and data addition are utilized to enhance generalization and stop overfitting. When deep learning models are taught, their work is evaluated by checking their memory, accuracy, precision, F1-score, confusion matrix, and AUC-ROC curve. Picking the best way is easier when you compare and contrast different models. Lastly, the learned model is used to divide people into three groups: those who are normal, those who are suspected, and those who have glaucoma medicine. To make sure the results are accurate and useful in real life, they are compared to assessments made by knowledgeable eye doctors. The study ends with a review of the results, with a focus on how they are better than current methods and what could be changed in the future to make finding glaucoma even easier.

Overview of the Approach

A structured approach is offered for grouping glaucoma diseases so that deep learning classifiers can quickly and correctly find the disease. Next, the D1 (ORIGA Image Dataset) is loaded. This has labeled shots of the retina. After that, an 80:20 split is used to make the collection into training and testing sets¹. Thus, there are similar numbers of cases with and without glaucoma in each set, allowing for a full model evaluation.

VGG16 is a deep learning model that is used for feature extraction, which makes the modeling of features better. Deep convolutional layers make the VGG16 model popular. It looks at retinal images and finds patterns that can help find glaucoma by using hierarchical features. Several models, including Naïve Bayes, K-Nearest Neighbors (KNN), Random Forest, Logistic Regression, and Decision Tree, use these extracted traits as inputs. Set up and train each classifier with the features that were taken, using its own pattern recognition and classification skills.

Testing the models with standard performance measures like accuracy, precision, recall, F1-score, and AUC-ROC shows how well they work at finding glaucoma. Comparative research picks the best classifier based on how quickly and accurately it can make predictions. This guarantees a solid method for screening for glaucoma automatically.

Dataset Description

The study uses two sets of data to try models for finding glaucoma. These are D1 consisting of the ORIGA Image Dataset and D2 comprising the ACRIMA Dataset. In this homogeneous collection, retinal images that have already been processed and have the same set of features are included. This makes sure that all algorithms give the same

results. The D1(ORIGA Image Dataset) is a public collection of 650 retinal images tagged with cup-to-disc ratio information. This makes it perfect for supervised learning. The D2 (ACRIMA Dataset) has 705 images, with 396 cases of glaucoma and 309 cases of normal vision. This gives us a wide range of pictures to test our model against. Together, these datasets make sure that training, testing, and performance benchmarking for using machine learning models to find glaucoma are all done well. Figure 2 shows how the work was done. The 1,2,3,...n models are Logistic Regression, Random Forest, SVM (Linear), SVM (RBF), K-Nearest Neighbors, Decision Tree, and Naive Bayes.

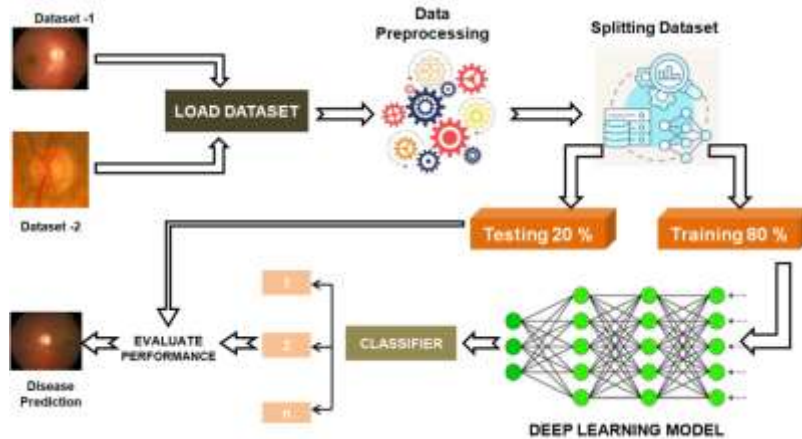


Fig 1: Flow chart of proposed work

Data Preprocessing

Preprocessing data is an important step in making sure that machine learning classifiers can use high-quality information to find glaucoma. The first step is feature extraction. A VGG16 model that has already been trained is used, and its deep convolutional layers are used to get hierarchical features from retinal images. The VGG16 model is loaded without the top classification layer (include_top=False), which makes sure that only useful feature maps are taken out. Before being sent through the network, the pictures are resized to the right size (input_shape=(IMG_SIZE, IMG_SIZE, 3)). The feature maps are smoothed to make a feature vector. This lets them work with well-known machine learning models like Naïve Bayes, Logistic Regression, Random Forest, SVM, KNN, Decision Tree, and Random Forest. You can define the flattened features if desired to make sure that all classifiers work the same way. This makes it easier to do jobs that involve classifying glaucoma.

Dataset Splitting

The information is split into 80% for training and 20% for testing so that the model can be trained and tested well. Machine learning classifiers are trained on the training set by learning patterns from the collected features. The testing set, on the other hand, checks how well the model can generalize to new data. This 80:20 split makes sure that there are an equal number of glaucoma and non-glaucoma cases, which lowers the risk of overfitting.

Stratified sampling is used to keep class levels the same during the splitting process. This makes sure that both the training and testing sets have the same number of positive (glaucoma) and negative (non-glaucoma) cases. This stops bias and makes the model more reliable. Later, deep learning-based feature extractors and machine learning models are taught on the split data. To ensure strong performance, metrics such as F1-score, AUC-ROC, accuracy, precision, and recall are used.

Classifiers Used

There were six machine learning algorithms that were used to sort retinal images for glaucoma. Each one used something different about itself to help with the recognition.

Logistic Regression: There is a simple and useful linear predictor that can figure out the likelihood of having glaucoma based on trait data. For jobs where you need to put things into two groups, it works great. Logistic regression helps find myopia by giving a framework for binary classification based on probabilities. The goal is to use information from a patient's medical records or a picture to figure out if they have glaucoma (label 1) or are healthy (label 0). Glaucoma risk is calculated using various factors, such as intraocular pressure (IOP), cup-to-disc ratio (CDR), retinal nerve fiber layer thickness, or traits from fundus images. According to the logistic regression model, the sigmoid function is used to guess the following:

$$P(y = 1|x; \theta) = h_{\theta}(x) = \frac{1}{1 + e^{-\theta^T x}} \quad (1)$$

The feature vector is x , and the weight vector is θ . These were learned during training. This tool gives it a number between 0 and 1, which is the chance of having glaucoma. If $h_{\theta}(x) \geq 0.5$, the patient is classified as glaucomatous.

Random Forest: Different decision trees are used in this type of group learning to make classification more accurate and reliable. Over fitting is lessened, and generalization is improved.

Random Forest improves the detection of glaucoma by using a group of decision trees to make classification more accurate and reliable. This is especially true when dealing with the complicated, non-linear relationships found in clinical and image-based data. Some of the things that are used to diagnose glaucoma are the intraocular pressure (IOP), the cup-to-disc ratio (CDR), the thickness of the retinal nerve fiber layer, and deep features taken from fundus or OCT pictures. A Random Forest works by training many decision trees, $T_1, T_2, \dots, T_k$. During training, each tree is taught on a different set of data and traits, by using bootstrap sampling. This makes the trees more diverse. In math, for each feature vector x that comes in, each tree T_i makes a forecast $h_i(x)$ that is in the range $[0,1]$. The Random Forest's final guess for binary classification is found by having all trees vote for it:

$$H(x) = \text{mode}(h_1(x), h_2(x), \dots, h_k(x)) \quad (2)$$

Support Vector Machine (SVM - Linear): A strong classifier that creates the best hyperplane to sort cases of glaucoma from those that don't have it. When there are a lot of dimensions in the feature space, the linear kernel works well.

Linear SVM is a strong supervised learning method used for binary classification tasks, like telling the difference between people who have glaucoma and those who are healthy.

In glaucoma detection, clinical parameters (e.g., intraocular pressure, cup-to-disc ratio) or features extracted from retinal fundus images are used as input vectors $x \in \mathbb{R}^n$. A linear SVM tries to find the best hyperplane that leaves the most space between the two

classes. To use math terms, a hyperplane is:

$$w^T x + b = 0 \quad (3)$$

where w is the weight vector orthogonal to the hyperplane, and b is the bias term. For linearly separable data, SVM maximizes the margin $\frac{2}{\|w\|}$ between the two classes by solving the following optimization problem:

$$\min_{w,b} \frac{1}{2} \|w\|^2 \quad \text{subject to} \quad y^{(i)}(w^T x^{(i)} + b) \geq 1, \forall i \quad (4)$$

where $y^{(i)} \in \{-1, 1\}$ is the class label for the i^{th} sample. In real-world glaucoma datasets, the classes are often not perfectly separable, so SVM uses a **soft margin** approach by introducing slack variables ξ_i to allow for some misclassifications, modifying the optimization as:

$$\min_{w,b,\xi} \frac{1}{2} \|w\|^2 + C \sum_{i=1}^m \xi_i \quad \text{subject to} \quad y^{(i)}(w^T x^{(i)} + b) \geq 1 - \xi_i, \xi_i \geq 0$$

(5)

Here, C is a regularization parameter that controls the trade-off between maximizing the margin and minimizing the classification error.

K-Nearest Neighbors (KNN): A distance-based algorithm that classifies images based on their similarity to neighboring samples. The choice of 'k' significantly impacts performance.

K-Nearest Neighbors (KNN) is a simple yet effective **non-parametric, instance-based learning algorithm** that can be applied to glaucoma disease detection by classifying a new patient based on the similarity to previously labeled cases. The idea is that patients with similar clinical or imaging features are likely to share the same diagnosis (glaucomatous or healthy). Given a new input vector x , which may include features such as intraocular pressure (IOP), cup-to-disc ratio (CDR), or texture and shape descriptors from retinal fundus images, KNN finds the **k** closest training samples in the feature space using a distance metric, most commonly **Euclidean distance**:

$$d(x, x^{(i)}) = \sqrt{\sum_{j=1}^n (x_j - x_j^{(i)})^2} \quad (6)$$

Once the distances to all training points are computed, the algorithm selects the k points with the smallest distances. The predicted class $\hat{y}$ for the input sample x is then determined by **majority voting** among the labels of these k -nearest neighbors:

$$\hat{y} = \arg \max_{c \in \{0,1\}} \sum_{i \in N_k(x)} \mathbb{I}(y^{(i)} = c) \quad (7)$$

where $N_k(x)$ is the set of indices of the k nearest neighbors, and $\mathbb{I}$ is the indicator function. In the context of glaucoma detection, if most of the closest patients in the training set were labeled as having glaucoma, the new case is classified as glaucomatous.

Decision Tree: A rule-based classifier that divides the data into groups based on how important each feature is. This makes the data easier to understand, but it can overfit if pruning methods are not used.

A Decision Tree is a tree structure that looks like a graph and is used for classification and regression tasks. It is easy to understand and works well for finding glaucoma diseases. In this case, the model is given information about things like age, IOP, CDR, retinal nerve fiber thickness, and other clinical or image-based markers. The Decision Tree method works by repeatedly dividing the dataset into smaller sets based on feature values that make the new groups as pure as possible. Each core node is a choice about a trait, each branch is the result of that choice, and each leaf node is a class label, like "glaucomatous" or "healthy."

It is normal to use Gini Impurity or Information Gain (based on Entropy) as a mathematical measure to choose the best feature for splitting. To find the Gini Impurity

$$Gini(D) = 1 - \sum_{i=1}^C p_i^2 \quad (8)$$

for a dataset D, do the following:

where p_i is the proportion of samples belonging to class i , and C is the total number of classes (for glaucoma, $C=2$). A feature that leads to the **largest reduction in impurity** is selected for the split. Alternatively, the **Entropy** of a dataset D is:

$$Entropy(D) = - \sum_{i=1}^C p_i \log_2(p_i) \quad (9)$$

and the **Information Gain** from splitting on feature A is:

$$Gain(D, A) = Entropy(D) - \sum_{v \in \text{Values}(A)} \frac{|D_v|}{|D|} Entropy(D_v) \quad (10)$$

where D_v is the subset of data where feature AAA has value vvv

Naïve Bayes: A probabilistic classifier that assumes feature independence. While efficient, its performance may be limited due to correlated features in medical imaging. Naïve Bayes is a probabilistic classifier based on Bayes' Theorem with a strong assumption that features are conditionally independent given the class. It works well for finding glaucoma when structured data like intraocular pressure, cup-to-disc ratio, and other clinical measures are used.

$$\hat{y} = \arg \max_{c \in \{0,1\}} P(C = c) \prod_{j=1}^n P(x_j | C = c) \quad (11)$$

Model Description

Vgg16

The ResNet101 model starts out with ImageNet pre-trained weights, but not for its final classification layer. Its job is to extract features from pictures of size (IMG_SIZE, IMG_SIZE, 3). Using the predict function, deep feature representations for both the training (X_train) and testing (X_test) datasets are generated in batches of 32.

$$S(i, j) = (I * K)(i, j) = \sum_m \sum_n I(i + m, j + n) \cdot K(m, n) \quad (12)$$

Where:

- $I(i+m, j+n)$ is a pixel from the input,
- $K(m, n)$ is a kernel weight,

- $S(i,j)$ is the output feature map value.

Resnet50

The ResNet50 model is loaded with ImageNet pre-trained weights without the top classification layer to extract features from images of size (IMG_SIZE, IMG_SIZE, 3). For both the training and testing datasets, the predict function is used to make feature

$$F(x) = H(x) - x \Rightarrow H(x) = F(x) + x \quad (13)$$

models in groups of 32.

Where:

- x : input to a layer block
- $F(x)$: residual (learned by convolutional layers)
- $H(x)$: desired output mapping

MobileNet

The MobileNetV2 model has ImageNet pre-trained weights but not the top classification layer. This lets it get small, useful features from pictures with dimensions (IMG_SIZE, IMG_SIZE, 3). The predict function is then used to generate feature vectors from the training and testing datasets, with batch sizes of 32. MobileNet is a computationally efficient convolutional architecture designed for mobile and embedded devices. It is hence more fitting in real-time glaucoma detection from retinal fundus images, either in remote-clinics or resource-oscared clinics. The chief idea behind MobileNet is the use of Depthwise Separable Convolutions which cut computational costs down tremendously while not sacrificing accuracy.

$$Cost_{standard} = D_K^2 \cdot M \cdot N \cdot D_F^2 \quad (14)$$

Where:

- MMM : input channels
- NNN : output channels
- DKD_KDK : kernel size
- DFD_FDF : spatial width/height of the feature map

DenseNet121

The input images are resized to (IMG_SIZE, IMG_SIZE, 3), and the model extracts deep features from the training (X_{train}) and testing (X_{test}) data using the predict function with a batch size of 32.

DenseNet121 (Dense Convolutional Network with 121 layers) is a deep CNN architecture that enhances glaucoma detection by promoting feature reuse and efficient gradient flow through dense connections. This makes it highly effective for analyzing complex retinal fundus images where fine structural changes (like in the optic nerve head) are critical for early glaucoma diagnosis.

$$x_l = H_l([x_0, x_1, \dots, x_{l-1}]) \quad (15)$$

Where:

- x_l : output of layer l
- $[x_0, \dots, x_{l-1}]$: concatenated feature maps from all preceding layers
- $H_l(\cdot)$: a composite function (BatchNorm $\rightarrow$ ReLU $\rightarrow$ Conv)

Performance Evaluation Metrics

To assess the effectiveness of the trained classifiers, multiple performance evaluation metrics are used. These metrics provide a comprehensive analysis of the model's ability to correctly classify glaucoma and non-glaucoma cases.

Accuracy: Measures the overall correctness of the model by calculating the ratio of correctly predicted cases to the total cases. While useful, accuracy alone may not be sufficient in imbalanced datasets.

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

Precision: Shows the percentage of cases correctly identified as glaucoma out of all cases thought to be glaucoma. It is very important for reducing false results in medical diagnosis.

$$\text{Precision} = \frac{TP}{TP + FP}$$

Recall (Sensitivity): This number shows how well the software can find glaucoma cases among all real glaucoma cases. A higher recall means fewer false positives, which is very important for finding diseases.

$$\text{Recall} = \frac{TP}{TP + FN}$$

F1-Score: The harmonic mean of accuracy and recall gives us a fair way to look at datasets that aren't all the same. In this way, both false positives and false negatives are kept to a minimum.

$$F1 - \text{score} = 2 * \frac{\text{Precision} * \text{Recall}}{\text{Precision} + \text{Recall}}$$

AUC-ROC Curve: The Receiver Operating Characteristic (ROC) graph compares the number of true positives (sensitivity) to the number of false positives to show how well the model can tell the difference. Area Under the Curve (AUC) shows how well the model works generally; values closer to 1 mean the model is better at classifying things.

Confusion Matrix: True positives (TP), false positives (FP), true negatives (TN), and false negatives (FN) are shown in this full breakdown of model predictions. This helps find patterns of wrong classification and makes model changes better.

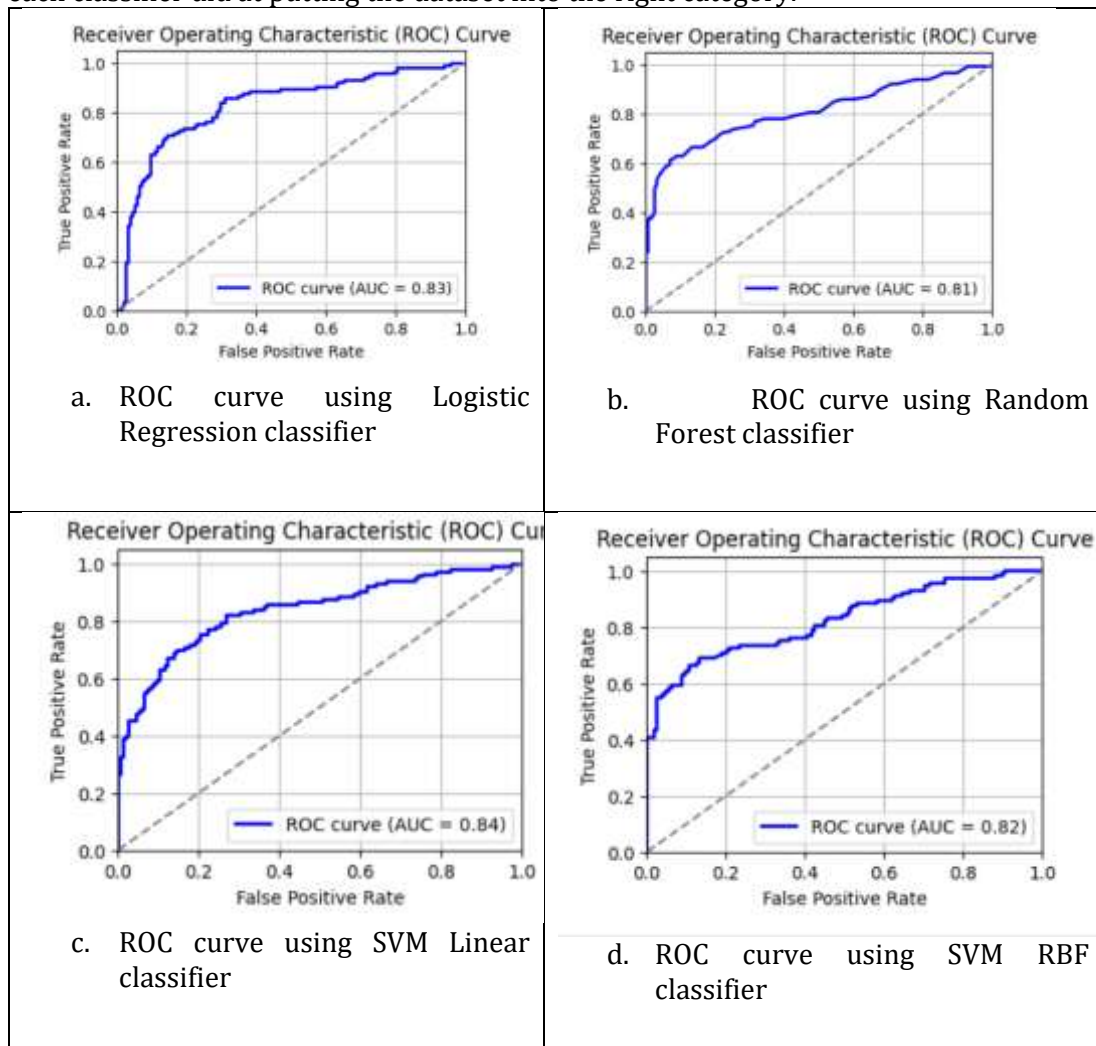
IV. Results

Table 1: Performance metrics of various classifiers applied to a model using VGG16

Model	Classifier	Accuracy	Precision		Recall		F1-score		AUC
			Normal	Glaucoma	Normal	Glaucoma	Normal	Glaucoma	
Vgg16	Logistic Regression	0.77	0.83	0.71	0.7	0.78	0.80	0.74	0.86
	Random Forest	0.81	0.80	0.82	0.89	0.69	0.84	0.75	0.86
	SVM (Linear)	0.77	0.82	0.71	0.77	0.77	0.80	0.74	0.86

	SVM (RBF)	0.78	0.75	0.89	0.95	0.57	0.84	0.69	0.82
	K-Nearest Neighbors	0.79	0.77	0.83	0.91	0.63	0.83	0.71	0.82
	Decision Tree	0.70	0.77	0.63	0.71	0.70	0.74	0.66	0.70
	Naive Bayes	0.66	0.72	0.59	0.70	0.61	0.71	0.60	0.66

Table 1 shows how well different classifiers worked when used on a model with VGG16 features. There are measures for each row that show how well the classifiers worked, such as accuracy and Area Under the Curve (AUC) for Receiver Operating Characteristic (ROC) curves. Logistic Regression, Random Forest, SVM (both Linear and RBF kernels), K-Nearest Neighbors, Decision Tree, and Naive Bayes were some of the models that were looked at. The accuracy ranges from 0.66 for Naive Bayes to 0.80 for Random Forest. The AUC ranges from 0.65 for Naive Bayes to 0.86 for Logistic Regression and SVM with Linear kernel. Based on the extracted VGG16 features, these measures show how well each classifier did at putting the dataset into the right category.



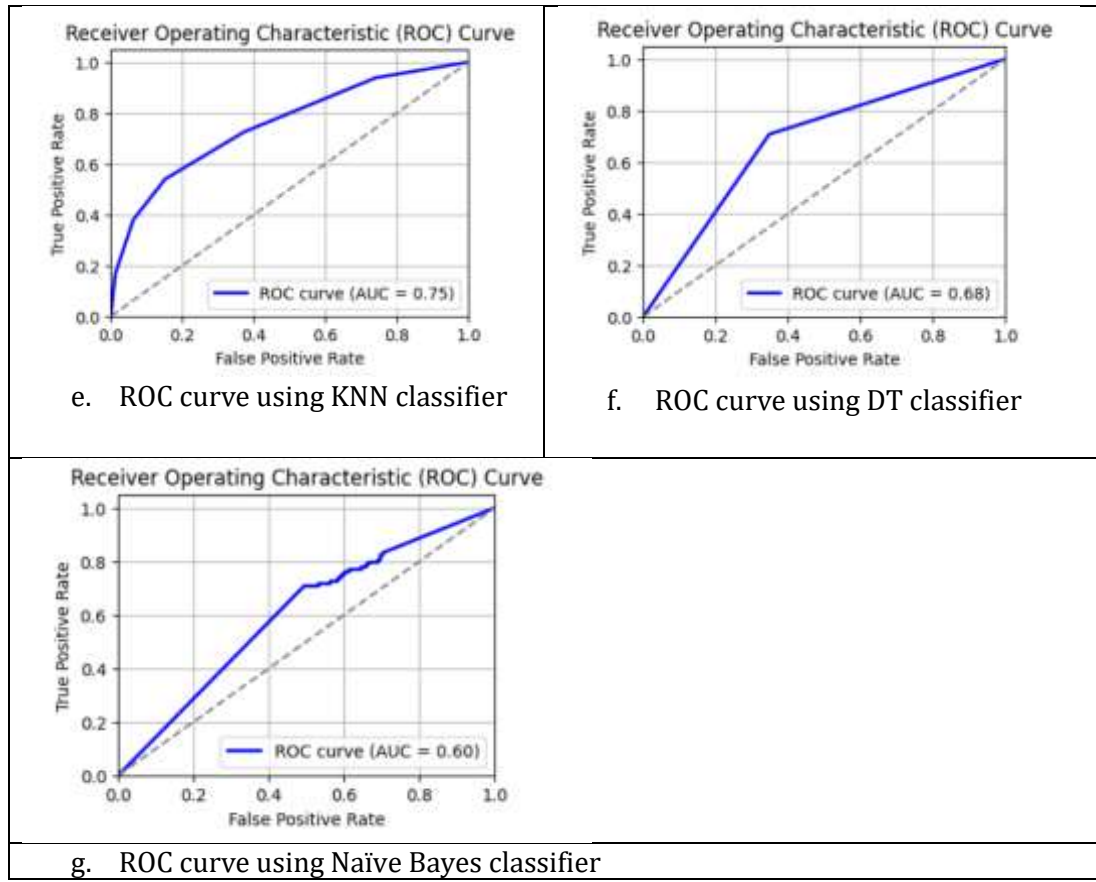


Fig 1: ROC curve using Vgg16 Model

Figure 1 shows the Receiver Operating Characteristic (ROC) curve for the VGG16 model for different classifiers, which show how well the different models do at classifying. The SVM with linear kernel achieved the highest AUC of 0.84, followed closely by Logistic Regression (0.83) and SVM with RBF kernel (0.82), suggesting excellent class separation. Random Forest also performed well with an AUC of 0.81, while KNN (0.75) showed moderate performance. In contrast, Decision Tree (0.68) and Naive Bayes (0.60) demonstrated lower effectiveness in distinguishing between the classes.

Table 2: Performance of different machine learning models using features extracted from ResNet50

Model	Classifier	Accuracy	Precision		Recall		F1-score		AUC
			Normal	Glaucoma	Normal	Glaucoma	Normal	Glaucoma	
ResNet50	Logistic Regression	0.74	0.79	0.67	0.75	0.73	0.77	0.70	0.84
	Random Forest	0.79	0.77	0.81	0.90	0.62	0.83	0.70	0.83
	SVM (Linear)	0.73	0.79	0.66	0.73	0.73	0.76	0.69	0.83
	SVM (RBF)	0.81	0.77	0.85	0.92	0.61	0.84	0.71	0.82

	K-Nearest Neighbors	0.76	0.74	0.77	0.88	0.57	0.80	0.65	0.80
	Decision Tree	0.69	0.75	0.61	0.69	0.68	0.72	0.64	0.69
	Naive Bayes	0.52	0.67	0.45	0.34	0.76	0.45	0.57	0.55

Table 2 shows the classification performance of different machine learning models using features extracted from ResNet50. Accuracy and AUC (Area Under the Curve) are reported for each classifier. Random Forest achieved the highest accuracy (0.78), while SVM (RBF) had a slightly better balance between accuracy (0.79) and AUC (0.81). Logistic Regression and SVM (Linear) performed moderately well with AUC values above 0.80. Decision Tree and K-Nearest Neighbors had lower performance, while Naive Bayes performed the worst, with accuracy at 0.51 and AUC at 0.55, indicating poor classification ability.

Table 3: Performance of different machine learning models using features extracted from MobileNet

Model	Classifier	Accuracy	Precision		Recall		F1-score		AUC
			Normal	Glaucoma	Normal	Glaucoma	Normal	Glaucoma	
Mobile Net	Logistic Regression	0.79	0.80	0.76	0.84	0.72	0.82	0.74	0.88
	Random Forest	0.80	0.81	0.79	0.87	0.71	0.84	0.75	0.84
	SVM (Linear)	0.78	0.81	0.74	0.82	0.73	0.81	0.74	0.87
	SVM (RBF)	0.73	0.81	0.64	0.70	0.77	0.75	0.70	0.83
	K-Nearest Neighbors	0.64	0.63	0.75	0.95	0.21	0.76	0.33	0.75
	Decision Tree	0.66	0.69	0.60	0.75	0.54	0.72	0.57	0.64
	Naive Bayes	0.65	0.71	0.57	0.67	0.61	0.69	0.59	0.64

Table 3 presents the performance of various classifiers using MobileNet-extracted features. Random Forest achieved the highest accuracy (0.80), while Logistic Regression

and SVM (Linear) had the highest AUC (0.87), indicating strong classification performance. SVM (RBF) showed moderate accuracy (0.72) with a decent AUC (0.83). K-Nearest Neighbors, Decision Tree, and Naive Bayes had lower accuracy, with Naive Bayes and Decision Tree performing the worst (AUC of 0.64). Overall, MobileNet combined with Logistic Regression or SVM (Linear) provided the best balance of accuracy and AUC.

Table 4: Performance of different machine learning models using features extracted from Densenet121

Model	Classifier	Accuracy	Precision		Recall		F1-score		AUC
			Normal	Glaucoma	Normal	Glaucoma	Normal	Glaucoma	
Densenet121	Logistic Regression	0.83	0.86	0.80	0.86	0.80	0.86	0.80	0.91
	Random Forest	0.82	0.81	0.84	0.91	0.70	0.85	0.76	0.87
	SVM (Linear)	0.83	0.85	0.80	0.86	0.79	0.86	0.79	0.90
	SVM (RBF)	0.84	0.82	0.86	0.92	0.73	0.87	0.79	0.88
	K-Nearest Neighbors	0.78	0.77	0.80	0.89	0.63	0.82	0.70	0.83
	Decision Tree	0.70	0.76	0.63	0.72	0.68	0.74	0.66	0.70
	Naive Bayes	0.64	0.74	0.56	0.59	0.71	0.66	0.62	0.65

Table 4 presents classification performance using features extracted from DenseNet121. Logistic Regression, SVM (Linear), and SVM (RBF) achieved the highest accuracy (0.83), with Logistic Regression having the best AUC (0.90). Random Forest also performed well with 0.81 accuracy and 0.87 AUC. K-Nearest Neighbors showed moderate performance (0.77 accuracy, 0.83 AUC). Decision Tree and Naive Bayes had the lowest performance, with Naive Bayes showing the weakest classification ability (0.64 accuracy, 0.65 AUC). Overall, DenseNet121 combined with Logistic Regression yielded the best classification results.

V. Conclusion

Leveraging two benchmark datasets—ORIGA (D1) and ACRIMA (D2)—the system benefits from diverse, preprocessed retinal images that support robust training, testing, and performance evaluation. Feature extraction using the pre-trained VGG16 model enhances the representation of retinal images by capturing deep, hierarchical features relevant to glaucoma detection. Multiple classifiers, such as Logistic Regression, Random

Forest, SVM, KNN, Decision Tree, and Naïve Bayes, are then given these traits. Among the models evaluated, DenseNet121 combined with SVM (RBF) achieved the highest accuracy of 84%, showcasing its superior capability in identifying glaucoma. This is followed by both ResNet50 with SVM (RBF) and VGG16 with Random Forest, each reaching an accuracy of 81%, indicating strong and consistent performance. MobileNet with Random Forest achieved a close 80% accuracy, highlighting its potential for lightweight, efficient deployment. The use of standard metrics such as accuracy, precision, recall, F1-score, and AUC-ROC ensures comprehensive evaluation of each model's diagnostic reliability. Future enhancements may include exploring ensemble methods, improving real-time inference capabilities, and extending the approach to larger, more diverse datasets for broader clinical applicability.

VI. References

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