



Machine Learning Algorithm Comparison for Four-Class Retinal Disease Classification Using Digital Fundus Images

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ABSTRACT

Retinal diseases are a major cause of vision loss, making timely and accurate diagnosis important for effective treatment. This study compares convolutional neural networks (CNN), k-nearest neighbors (K-NN), and support vector machines (SVM) for classifying digital fundus images into four categories: normal retina, cataract, glaucoma, and other retinal diseases. The models are evaluated using accuracy, sensitivity, specificity, positive predictive value, negative predictive value, and F-score. CNN achieves the highest reported accuracy (94.05%) and sensitivity (0.9977), with an F-score of 0.9693. The results indicate that CNN can be useful for automated retinal screening, while its low specificity (0.0178) highlights the need to reduce false-positive predictions. The comparison illustrates both the potential and the limitations of machine-learning-based retinal disease classification.

Keywords: Retinal diseases ▪ Machine learning ▪ Convolutional neural networks ▪ Fundus images ▪ Disease classification ▪ Ophthalmology

1. INTRODUCTION

Advances in retinal imaging and computational analysis have expanded the possibilities for objective assessment of ocular disease. Optical coherence tomography and adaptive-optics imaging can reveal retinal structures at increasingly fine scales, while automated analysis can help clinicians screen the growing volume of retinal images. These developments are relevant to conditions including age-related macular degeneration, diabetic retinopathy, cataract, and glaucoma, which contribute substantially to visual impairment and healthcare burden [1, 2, 3, 4, 5, 6, 7].

Early diagnosis can enable timely treatment and help prevent avoidable vision loss. Conventional image assessment depends on specialist interpretation and may vary between observers; the workload can also limit access to screening, particularly in underserved settings. Machine-learning systems

offer the potential to process images consistently and at scale, supporting rather than replacing clinical assessment [8, 9, 10]. Retinal classification has been approached using conventional algorithms, including SVM and K-NN, as well as deep-learning models that learn image representations directly. CNNs can identify hierarchical patterns in fundus images, and ensemble or multimodal systems can combine learned image features with other diagnostic information. These approaches have been investigated for diabetic retinopathy, glaucoma, and multiple retinal conditions [11, 12, 13, 14, 15, 16, 17].

Practical deployment also depends on image quality, representative training data, class balance, generalization across cameras, and integration into clinical workflows. Remote monitoring, mobile screening, augmentation, and transfer learning are among the approaches explored to address these issues [18, 19, 20, 21, 22, 23, 24, 25]. In this study, CNN, K-NN, and SVM are compared for four-class classification of

retinal fundus images. The reported results emphasize sensitivity and accuracy while also exposing a marked specificity trade-off for the CNN model.

The source article places this classification problem in the broader context of retinal imaging. Optical coherence tomography provides cross-sectional views of retinal layers, while fundus photography and other imaging modalities contribute complementary information. Age-related macular degeneration, diabetic retinopathy, glaucoma, and inherited retinal diseases are among the conditions that motivate scalable imaging and screening services [1, 2, 4, 6, 26]. Population ageing and the effects of visual impairment on productivity, disability, and quality of life further increase the need for accessible diagnostic services.

Timely identification can support care before irreversible damage occurs. Recent reviews examine artificial-intelligence methods for diabetic retinopathy and macular edema, age-related macular degeneration, and glaucoma screening and management [8, 9, 10, 11, 23]. Conventional image review, however, depends on specialist interpretation and may create delays when screening volumes exceed available clinical capacity [2, 7].

Machine-learning systems can support the analysis of large image collections, but their performance depends on image quality, representative data, and validation across settings. Reviews of fundus- and OCT-based screening identify these issues as important considerations for clinical use [1, 7, 13, 19].

Conventional methods such as SVM and K-NN have been studied alongside CNNs and hybrid models that learn image features directly. Recent work has applied deep learning to fundus and OCT images for multiple disease categories as well as condition-specific screening [11, 12, 13, 14, 15, 18, 25, 27]. Classification remains challenging because visible findings vary across conditions: diabetic retinopathy may show microaneurysms, hemorrhages, or exudates; glaucoma involves optic-nerve changes; and inherited retinal disorders require disease-specific interpretation of imaging features [6, 26].

The article also reviews deployment considerations. Remote screening and broader access to fundus imaging can be supported by automated systems, but image quality, dataset size, class balance, and generalization across acquisition conditions remain important [7, 13, 17, 19, 20, 21, 22, 24]. Integration into clinical workflows also requires interpretable, validated tools that support clinician review [2, 16, 23].

2. LITERATURE REVIEW

Artificial intelligence has been applied to ocular diagnosis through both conventional machine-learning models and deep neural networks. Earlier classification methods such as SVM and K-NN use engineered representations or similarity measures, while CNNs learn multi-level image features that can capture vascular patterns, optic-disc structure, and other signs of pathology. Recent work has also examined attention-based and residual architectures, inherited retinal disease diagnosis, segmentation of OCT images, and image-based systems for clinical decision support.

The literature further considers data augmentation and trans-

fer learning for small or imbalanced datasets, anomaly detection and few-shot learning for rare conditions, and the use of fundus or OCT images in screening. Despite reported progress, differences in datasets, acquisition conditions, and evaluation protocols make direct comparisons difficult. Table 1 summarizes studies [26]–[39].

Recent comparative work has evaluated deep models for fundus-image diagnosis using large datasets. One 2024 study introduced the EDDFS dataset, containing 28,877 fundus images, and benchmarked models on single-label and multi-label diagnostic tasks [27]. Another study examined data-efficient CNN classification of retinal disease from fundus photographs, emphasizing performance with limited training data [28].

For inherited retinal diseases, fundus photography, optical coherence tomography, and other imaging modalities can reveal complementary structural findings. A recent review describes how these imaging features support characterization and longitudinal assessment of inherited conditions [26]. Beyond image-level accuracy, retinal disease affects daily activities and psychological well-being, motivating systems that support timely intervention and patient-centered care [29]. Deep-learning screening systems may process images rapidly and help prioritize cases for referral, while code-free model development could make these tools more accessible to clinicians; both approaches still require validation, quality assurance, and regulatory consideration [30, 31].

Automated retinal-layer segmentation in diseased OCT images is challenging because of low image quality, similar layer morphology, and variation in lesion shape and size. HDB-Net combines global context from a Swin Transformer with local features from ResNet-50 and uses boundary-aware features to improve segmentation in pathological OCT images [32]. Related work considers AI support for precision treatment, including laser therapy in ischemic retinal disease, and machine-learning analysis of OCT to improve consistency and reduce delays associated with manual interpretation [33, 34].

Transfer learning with VGG16, DenseNet201, InceptionV3, and Xception, combined with Bayesian hyperparameter optimization and augmentation, has been explored for multi-disease OCT classification [35]. Anomaly-detection systems may identify referable diabetic retinopathy or unusual presentations even when trained primarily on non-referable cases [36]. Fundus-image comparisons have reported 87.42% accuracy for a ResNet50-based nine-class model [37]; generative augmentation with few-shot learning has also been studied for rare retinal diseases [38]. Finally, multiscale deep learning on OCT images has been applied to diabetic macular edema and other retinal conditions, with adaptive preprocessing and triage proposed to address image-quality variation and clinical workload [39].

Overall, the reviewed work points to the potential of automated ocular diagnostics, while identifying the need for standardized evaluation and large, high-quality datasets. Random forests, decision trees, CNNs, and other approaches have been explored for early detection and decision support; further validation is needed before these systems can be generalized across clinical settings.

3. MATERIALS AND METHODS

Table 1. Machine and Deep Learning for Retinal Disease Diagnosis: A Comparative Analysis

Ref.	Main focus	Methodology	Key findings
[27]	Multi-disease diagnosis from fundus images.	Benchmarking deep models with the EDDFS dataset.	Introduced a 28,877-image dataset and benchmarks for single- and multi-label tasks.
[28]	Data-efficient retinal disease classification.	CNN-based classification of conventional fundus images.	Evaluated disease classification with reduced training-data requirements.
[26]	Imaging findings in inherited retinal diseases.	Review of multimodal retinal imaging.	Summarized imaging features relevant to diagnosis and follow-up.
[29]	Imaging-based machine learning in retinal-disease management.	Review of machine-learning applications and therapeutic technologies.	Reviewed imaging and ML approaches for AMD, diabetic retinopathy, and other conditions.
[30]	Early detection of multiple retinal diseases.	Deep-learning algorithms for retinal fundus images.	Supports rapid diagnosis and treatment planning using deep-learning models.
[31]	Code-free deep learning versus expert-designed models.	Comparison of code-free and bespoke models for retinal pathologies in OCT.	Compared the discriminative performance of code-free models with expert-designed models.
[32]	Retinal-layer segmentation in diseased OCT images.	HDB-Net with Swin Transformer and ResNet-50 branches.	Combined global context, local features, and boundary awareness for pathological OCT segmentation.
[33]	Guiding laser therapy in ischemic retinal disease.	Deep learning for precision medicine.	Examined precision-medicine support for laser therapy.
[34]	Clinical interpretation of retinal disease using OCT.	Machine learning applied to OCT image analysis.	Focused on machine-learning support for clinical image interpretation.
[35]	Retinal-disease diagnosis from OCT images.	Bayesian-optimization deep-learning network.	Examined automated approaches to improve diagnostic precision.
[36]	Detection of retinal-disease anomalies.	Generative, discriminative, and self-supervised deep learning.	Developed anomaly-detection approaches for retinal diagnosis.
[37]	Diagnostic tools for multiple retinal diseases.	Fundus-image-based deep learning.	Explored AI diagnostic platforms using retinal fundus images.
[38]	OCT diagnosis of rare retinal diseases.	Few-shot learning with a generative adversarial network.	Reported improved applicability of deep learning to rare diseases.
[39]	Diabetic macular edema and other retinal diseases.	Multiscale deep learning using OCT.	Applied deep learning to OCT-based retinal-disease diagnosis.

3.1 Dataset

The study uses a retinal image dataset obtained from Kaggle ([Kaggle Eye Disease Classification dataset](#)). Images are grouped into four classes: normal retina, cataract, glaucoma, and other retinal diseases. The categories represent visually distinct conditions for model training and evaluation. The source article does not specify the number of images per class or the train–test split.

Figures 1–4 show examples of the four image categories used to illustrate normal retinal appearance and disease-related variation. The healthy fundus in Figure 1 provides a reference for the disease examples. Figure 2 illustrates the opacity associated with cataract, which reduces light transmission; Figure 3 represents glaucoma-related optic-nerve changes associated with elevated intraocular pressure; and Figure 4 shows other visible variations in retinal structure, color, and texture.

3.2 Convolutional Neural Network

CNNs are deep neural networks designed to learn spatial features from images through convolutional filters. In retinal

**Figure 1.** Image of a healthy retina.

classification, early layers can represent edges and textures, while deeper layers combine these patterns to encode more complex structures. Unlike conventional methods that depend on manually designed features, CNNs learn hierarchical image representations during training.

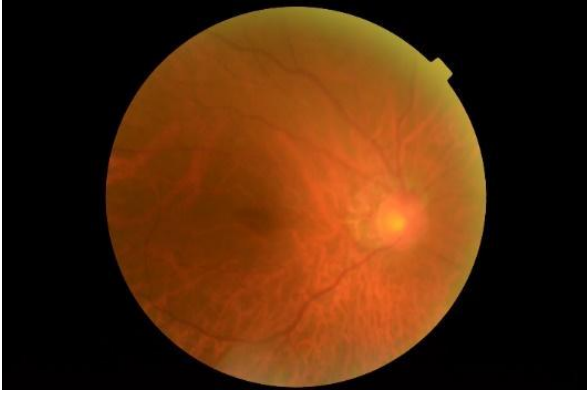


Figure 2. Cataract disease.



Figure 4. Retinal disease.

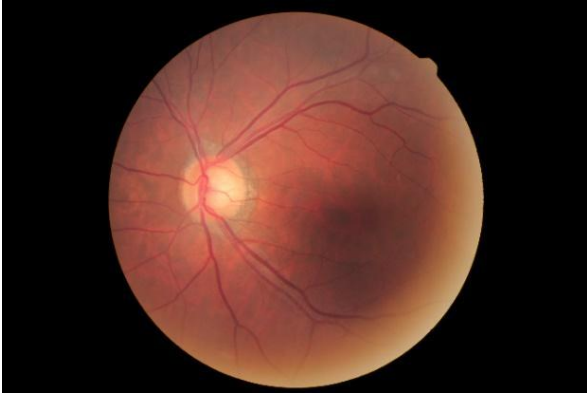


Figure 3. Glaucoma disease.

3.2.1 Mathematical Foundation

The discrete convolution of an image I with a kernel K is

$$(I * K)(i, j) = \sum_m \sum_n I(i - m, j - n) K(m, n). \quad (1)$$

In practical CNN implementations, cross-correlation is commonly used:

$$(I \star K)(i, j) = \sum_m \sum_n I(i + m, j + n) K(m, n). \quad (2)$$

For a multi-channel input, the k -th output feature map is

$$Y_{i,j}^{(k)} = \sigma \left(\sum_{c=0}^{C-1} \sum_{m=0}^{M-1} \sum_{n=0}^{N-1} X_{i+m, j+n}^{(c)} W_{m,n,c}^{(k)} + b^{(k)} \right), \quad (3)$$

where $X^{(c)}$ is input channel c , $W^{(k)}$ denotes the learnable filter weights, $b^{(k)}$ is a bias, and σ is an activation function.

3.2.2 Architecture Components

Convolutional layers apply learnable filters to identify local patterns. For input size I , padding P , kernel size K , and stride S , the output feature-map size is

$$O = \left\lfloor \frac{I + 2P - K}{S} \right\rfloor + 1. \quad (4)$$

Pooling reduces spatial dimensions and computational cost. Max pooling and average pooling over a region $R_{i,j}$ are de-

fined respectively as

$$y_{i,j} = \max_{(m,n) \in R_{i,j}} x_{m,n}, \quad (5)$$

$$y_{i,j} = \frac{1}{|R_{i,j}|} \sum_{(m,n) \in R_{i,j}} x_{m,n}. \quad (6)$$

The rectified linear unit (ReLU) is $f(x) = \max(0, x)$. Variants include Leaky ReLU, $f(x) = \max(\alpha x, x)$, where α is a small positive constant; parametric ReLU, $f(x) = \max(\alpha_i x, x)$, where the slope is learned; and Swish, $f(x) = x \sigma(\beta x) = x / (1 + e^{-\beta x})$.

3.2.3 Advanced Architectural Innovations

Residual networks use skip connections to facilitate training deeper models:

$$y = F(x, \{W_i\}) + x. \quad (7)$$

Attention mechanisms weight the relative importance of image features:

$$\text{Attention}(Q, K, V) = \text{softmax} \left(\frac{QK^T}{\sqrt{d_k}} \right) V. \quad (8)$$

Dense connections allow each layer to use the preceding feature maps:

$$x_\ell = H_\ell([x_0, x_1, \dots, x_{\ell-1}]). \quad (9)$$

These designs can improve feature reuse and help the network focus on relevant retinal regions.

3.2.4 Medical Imaging Adaptations

Transfer learning fine-tunes a model pretrained on a large dataset for a medical task:

$$\theta_{\text{medical}} = \arg \min_{\theta} [L_{\text{medical}}(\theta) + \lambda \|\theta - \theta_{\text{pretrained}}\|_2^2], \quad (10)$$

where λ controls regularization toward the pretrained weights. Image augmentation can include geometric transformations (rotation, scaling, and translation), photometric adjustments (brightness, contrast, and gamma), and domain-specific operations such as vessel enhancement or optic-disc centering. Class imbalance may be addressed with weighted or focal

loss, or synthetic minority oversampling (SMOTE).

$$L_{\text{weighted}} = -\sum_i w_i y_i \log(\hat{y}_i),$$

$$L_{\text{focal}} = -\alpha_t (1 - p_t)^\gamma \log(p_t).$$

3.2.5 Regularization and Optimization

Dropout randomly disables units during training:

$$r_i \sim \text{Bernoulli}(p), \quad \tilde{y}_i = r_i y_i. \quad (11)$$

Batch normalization uses mini-batch statistics to normalize and rescale activations:

$$\hat{x}_i = \frac{x_i - \mu_B}{\sqrt{\sigma_B^2 + \epsilon}}, \quad y_i = \gamma \hat{x}_i + \beta. \quad (12)$$

Weight decay adds an L_2 penalty to the original objective:

$$L_{\text{total}} = L_{\text{original}} + \lambda \sum_i w_i^2. \quad (13)$$

Model deployment also requires attention to computational cost and interpretability. Pruning, quantization, and knowledge distillation can reduce model size and inference requirements.

4. RESULTS

The study compares CNN, K-NN, and SVM for classifying fundus images into normal, cataract, glaucoma, and other retinal disease categories. The reported evaluation metrics are accuracy, sensitivity, specificity, positive predictive value (PPV), negative predictive value (NPV), and F-score. Table 2 reproduces the values reported in the source article.

Table 2. Machine Learning Model Results for Retinal Diseases

Model	Accuracy	Sens.	Spec.	PPV	NPV	F-score
CNN	0.9405	0.9977	0.0178	0.9424	0.3333	0.9693
K-NN	0.9165	0.5310	0.9423	0.3820	0.9677	0.4444
SVM	0.8946	0.5310	0.9259	0.3820	0.9582	0.4444

Figure 5 presents mean performance metrics with error bars; Figure 6 shows a kernel-density estimate of accuracy; and Figure 7 compares overall accuracy across the three models.

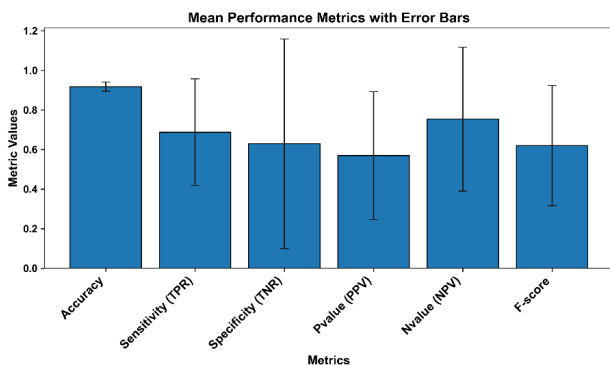


Figure 5. Mean performance metrics with error bars.

CNN has the highest reported accuracy and sensitivity, as well as the highest F-score. Its specificity is only 0.0178, however, indicating a substantial false-positive trade-off in the reported

results. K-NN and SVM have lower sensitivity (0.5310) but higher specificity (0.9423 and 0.9259, respectively). The results should therefore be interpreted across all metrics rather than by accuracy alone.

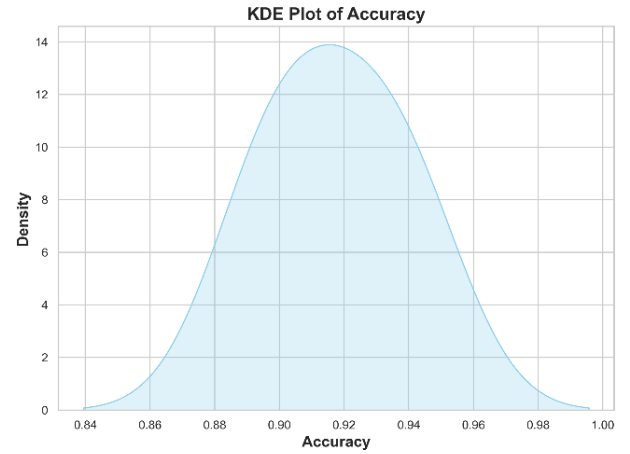


Figure 6. Kernel-density estimate (KDE) plot of accuracy.

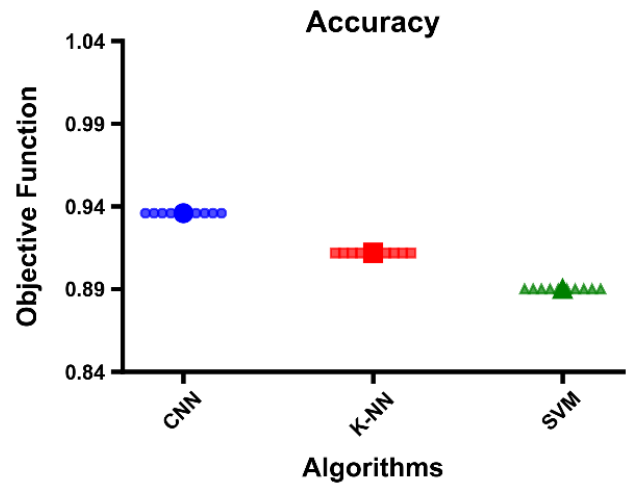


Figure 7. Accuracy comparison for all models.

5. CONCLUSION

This study compares CNN, K-NN, and SVM for four-class retinal disease classification using digital fundus images. CNN achieves the highest reported accuracy (94.05%), sensitivity (0.9977), and F-score (0.9693), suggesting potential for screening support. At the same time, its reported specificity (0.0178) is very low and indicates that false-positive performance requires substantial improvement. K-NN and SVM have lower sensitivity despite their higher specificity. Future work should refine model thresholds and training, assess performance on broader datasets, and validate the approach in clinical settings.

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