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Eye Disease Classification Using Deep Learning Algorithms

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Abstract: *Diabetic eye conditions, including diabetic retinopathy, cataracts, glaucoma, and other retinal conditions, remain the leading causes of preventable blindness worldwide. Detection and classification to a stage are essential to early intervention, yet manual classification is labor-intensive, resource-wasteful, and human-error-prone. This paper describes an implementation of a deep learning automatic multi-class classifier from Convolutional Neural Network (CNN) with Vgg19 and ResNet101 architectures. The model is tested and trained over a Kaggle dataset of four classes: normal, cataract, glaucoma, and retina disease images. Data processing steps like image resizing (256x256 pixels), contrast stretch, and normalization are applied over the data to achieve consistent input quality. 75% of the data is used to train the model and 25% for testing to guarantee that the model undergoes a solid test. Performance measures are precision, recall, accuracy, and F1-score to measure the model's performance. Out of the architectures experimented with, ResNet101 performs the best since its residual learning mechanism avoids vanishing gradients and deepens feature extraction. It addresses significant challenges such as model interpretability, image variability, and data imbalance required for clinical deployment. The system to be designed assists medical professionals by simplifying the diagnosis process, reducing manual intervention, and improving diagnostic consistency. The research contributes to the evolution of diagnostic systems based on AI by delivering a scalable, secure, and precise diabetic eye disease classifier. A couple of potential directions for the future include increasing additional data in the dataset, applying attention mechanisms, and deploying the model on edge devices for point-of-care real-time diagnosis*

Keywords: Diabetic retinopathy, Deep learning, Convolutional Neural Networks (CNN), Vgg19, ResNet101, Medical image classification

I. INTRODUCTION

The rising prevalence of diabetes and other systemic diseases has significantly increased the burden of blindness and visual impairment worldwide. Among all the diabetic eye diseases, diabetic retinopathy, cataracts, glaucoma, and other retinal disorders are reported to be among the major causes of preventable visual loss. These conditions tend to develop slowly and for symptoms to be evident only after considerable damage has been inflicted. Thus, early diagnosis and prompt treatment are the key to preserving vision. However, the conventional way of detecting diabetic eye diseasesmanual retinal image inspection by ophthalmologistsis labor-intensive and not scalable. Such procedures are prone to human error and variation in interpretation, especially in areas lacking skilled personnel. With over 93 million people expected to be impacted by diabetic retinopathy globally, the demand for faster, more accurate, and automated diagnostic techniques has never been more acute.

The development of Artificial Intelligence (AI) and, in particular, Deep Learning (DL) has revolutionized the analysis of medical images. Both have shown unprecedented capabilities for automating disease detection and classification by identifying subtle and imperceptible visual patterns beyond the human eye. Convolutional Neural Networks (CNNs) are a leading architecture in this space because they can learn spatial hierarchies of features with convolutional layers and be trained to do so. CNNs are especially good at processing large image data sets, outperforming standard machine learning models at classification. Their capacity for pattern generalization over texture, color, and intensity variance renders them ideally suited for diabetic eye disease diagnosis from retinal fundus images, which are typically associated with multi-class discrimination and high performance in diagnosis.

While CNNs have found great success in most classification tasks, it is challenging to develop a perfect model for auto-classifying diabetic eye disease. First, the input images vary highly in quality, resolution, and contrast, affecting the model's uniformity. Second, the datasets employed are not balanced, such that some conditions, e.g., 'normal' images, are abundant while others, e.g., glaucoma and retina-related conditions, are sparse. The consequence is biased learning patterns and higher misclassification rates for minority classes. Third, distinguishing visually comparable diseases such as cataracts and glaucoma requires models to learn subtle details in the images. Lastly, models must be accurate, explainable, and lightweight for medical use to be incorporated into real-time diagnostic systems.

Considering these issues, this study attempts to create a deep learning classifier system that automatically identifies and differentiates between most diabetic eye diseases. The system utilizes three architectures: a specially designed Convolutional Neural Network, Vgg19, and ResNet101. The models are trained and tested on Kaggle's four big class datasets with standard, cataract, glaucoma, and retina diseases. For consistency and strength maintenance, preprocessing methods such as resizing the image to 256x256 pixels, brightness normalization, and contrast enhancement are carried out. Data is also augmented through rotation, flip, and zoom to add more variability and alleviate the issue of data imbalance.

Vgg19, a well-established deep network consisting of 16 convolutional and three fully connected layers, is used due to its structured simplicity and high performance in image recognition. It uses small 3×3 filters and a uniform architecture design, so it is a suitable candidate for transfer learning and feature extraction of medical images. Vgg19, though, is afflicted by deeper representations due to the vanishing gradient problem. To make up for this, ResNet101 is proposed—a residual learning-based 101-layer architecture composed of identity shortcut connections. These enable deeper networks to be trained with minimal decrease in performance. ResNet101 is effective at feature extraction as it preserves gradient flow between layers so that the network can learn fine features required to distinguish between comparable patterns of eye disease.

The proposed models are contrasted with default performance metrics: accuracy, precision, recall, and F1-score. These broad measures assess the model's performance in specific and imbalanced datasets where accuracy may not be sufficient. Based on preliminary comparisons, ResNet101 is better than CNN and Vgg19, with maximum accuracy and balanced performance across all classes. Its deep architecture and residual connections can account for this, which promotes generalization and reduces overfitting.

The value of this research lies in its ability to provide an affordable and scalable solution to a pressing healthcare issue. By simplifying the classification process, the system presented can alleviate the burden on ophthalmologists, especially in low-resource environments, and ensure timely proper diagnosis and treatment. Besides, explainable deep learning models' applications promote the validity of medical doctors and ease the integration of AI-assisted diagnosis into clinical workflows. The refined system can further be executed on edge devices like Raspberry Pi or embedded in web-based interfaces to enable real-time diagnosis, giving it great versatility in use-case applications.

Within the broader context of AI for healthcare, this paper contributes to the evidence that deep learning is suitable for complicated diagnostic tasks. The paper demonstrates that given the appropriate model choice, preprocessing, and performance estimation, AI systems can rival or surpass human-level performance in diabetic eye disease detection. It further opens new avenues for generalizing the work to other eye conditions and leveraging attention methods or ensemble strategies to enhance robustness.

In short, this research addresses a critical healthcare challenge with cutting-edge deep learning approaches. Through combining bespoke CNNs, Vgg19, and ResNet101 and their validation on a multi-class retinal disease database, the study sets the stage for developing intelligent diagnosis systems that are efficient, accurate, and practically applicable in a clinical setting. The system's capacity to discern multiple eye ailments improves diagnostic efficiency and facilitates timely intervention and control of vision-destructive diseases. While the demand for computerized diagnostic aids continues to grow, this research offers a new solution that balances technological developments with reality-based utility in ophthalmology.

II. LITERATURE SURVEY

Wejdan L Alyoubi and others [1] in 2020 used diabetic retinopathy analysis using deep learning methods. They used binary, lesion-based, and vessel-based classification techniques and tested their performance using Convolutional Neural Networks (CNNs). They analyzed various datasets and estimated the approximate accuracy of the results. The authors also explained the application of CNNs in diabetic retinopathy analysis of images, including five feature analyses from fundus images. Most image processing-based medical diagnostic systems employ deep learning to ensure improved and precise analysis results.

Vijay Kumar G. et al. [2] (2019) emphasized diagnosing diabetic retinopathy using a neural network-based system. Their research used computer vision, machine learning, and deep learning models to categorize a properly prepared dataset. Several approaches like Support Vector Machines (SVM), multi-class perceptron neural networks, and Convolutional Neural Networks (CNN) were used to analyze recognition performance. In addition to enhancing the reliability and stability of the results, feature extraction procedures and cross-fold validation were also used in the method proposed by the researchers.

Xiaomeng Li et al. [3] proposed a novel CANET model for detecting diabetic retinopathy. Their approach, the Cross Disease Consideration Network (CDCN), considers DR and DME simultaneously by looking into their intrinsic relationship and morphological characteristics. The CDCN model has two major components: an expert module for normalizing normal and abnormal fundus images to identify key retinal lesion features and an auxiliary module to analyze the correlation between two independent datasets' extracted features. Integration of the two modules enhances feature extraction capacity, leading to better diagnostic performance for both DR and DME. To validate the proposed approach, the authors used two well-known benchmark datasets, i.e., the ISBI 2018 IDRiD challenge dataset and the Messidor dataset.

Lei Zhang et al. [4] suggested a stable method for proliferative diabetic retinopathy (PDR) detection using a double-sided morphology-based thresholding method coupled with a matched filter. PDR, an advanced diabetic complication that may cause vision loss, should be detected early to protect the vision of diabetic patients. Neovascular structure formation marks the beginning of PDR, and it can be detected using retinal vessel extraction methods. Their approach employs an integrated filter that carries out local cross-sectional examination of retinal vessels and double-sided thresholding to minimize false positives in detecting irregular vessel edges. This altered filter enhanced vessel detection accuracy while considerably reducing false detection rates.

Sohini R. and team [5] 2014 conducted a study using a machine learning-based method combined with AI methods to analyze diabetic retinopathy. They proposed an automated computer-assisted system to screen fundus images that effectively managed the discrepancies in brightness and finally classified diabetic retinopathy severity through AI-based algorithms. Classifiers like the Gaussian Mixture Model (GMM), k-nearest Neighbors (kNN), Support Vector Machine (SVM), and AdaBoost were used for discriminating lesions from non-lesion regions. Of these, GMM and kNN were found to have better classification accuracy. Applying AdaBoost in feature selection to successfully decrease the original 78 features to just 30 of the most significant ones for detecting lesions stood out as unique in this research. The authors presented a new two-stage classification process: the non-lesion areas were removed in the first stage, and the second stage classified further white lesions (hard exudates and cotton wool spots) and red lesions (hemorrhages and microaneurysms). The system was tested against 1,200 images of the publicly accessible MESSIDOR database.

Sheikh M. Saiful Islam et al. (2018) [6] proposed a novel technique for the early diagnosis of Diabetic Retinopathy (DR) using deep learning algorithms. DR is a progressively chronic disease and a leading cause of blindness and visual impairment. Overlapping between different stages of DR and the co-occurrence of numerous features hinder the diagnosis. Additionally, traditional methods of DR diagnostics are complex, time-consuming, and highly skill-biased for the doctor. This is precisely why computer-based detection programs are used to avoid such misery. The CNN model created in the research could accurately detect microaneurysms (MAs) and other significant symptoms of DR, effectively annotating retinal fundus images, which play a crucial role in early detection and treatment.

Zago et al. [7] proposed a scheme that involves two convolutional neural networks (CNNs), namely a pre-trained VGG16 and a self-trained CNN, to distinguish between fundus images with and without Diabetic Retinopathy (DR) from lesion patch probabilities. The training was carried out using the DIARETDB1 dataset, whereas evaluation was

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done on various datasets such as IDRiD, Messidor, Messidor-2, DDR, DIARETDB0, and Kaggle. Out of them, the Messidor dataset attained maximum performance, and its sensitivity came to 0.94, along with an AUC of 0.912.

Jiang et al. [8] proposed a model that employed three Convolutional Neural Networks (Inception-v3, ResNet152, and Inception-ResNet-v2) for the classification of fundus images into referable and non-referable diabetic retinopathy (DR) classes. The images were resized, augmented, and enhanced before training. The model was also enhanced through the Adaboost algorithm, and the Adam optimizer was employed to update the network weights. With this method, an accuracy of 88.21% and an AUC score of 0.946 were attained.

Wang et al. [9] employed three different pre-trained CNN models, namely VGG16, AlexNet, and Inception-v3, in classifying DR into five categories based on the Kaggle fundus image database. All models were given the resized fundus images in conformation to each model's respective input specifications. On testing, Inception-v3 performed highest with an accuracy of 63.23%, followed by 50.03% for VGG16 and 37.43% for AlexNet.

Pratt et al. [10] used a deep learning model in the form of a CNN with 10 convolutional layers, eight max-pooling layers, three fully connected layers, and a softmax classifier to classify fundus images of the Kaggle dataset into five diabetic retinopathy (DR) severity classes. The color fundus images were normalized and resized before training. L2 regularization and dropout methods were used to avoid overfitting. The system obtained 95% specificity, 75% accuracy, and 30% sensitivity.

Wang et al. [11] proposed a hybrid method of hard exudate lesion detection by combining handcrafted features and features from a CNN with an RF classifier. It was tested on the HEI-MED and E-ophtha datasets. The processing pipeline involved cropping, normalization, morphological processing, and dynamic thresholding to obtain candidate regions. Their CNN model had three convolutional and pooling layers and a single fully connected layer for feature extraction. Their proposed model achieved AUC of 0.9323 and 0.9644 and related sensitivity values of 0.9477 and 0.8990 for HEI-MED and E-ophtha datasets, respectively.

Hua et al. [12] removed retinal vessels from images of the DRIVE dataset by employing a pre-trained model, ResNet-101. Four feature maps of the network were chosen and placed, each at a time, to form one combined map. The data was augmented on fundus images before CNN processing. Substantial performance results were achieved: accuracy = 0.951, sensitivity = 0.793, AUC = 0.9732, and specificity = 0.9741.

While enormous progress has been achieved in diabetic retinopathy diagnosis with the help of deep learning, loopholes in research continue to persist in some areas. The main limitation is that there has not been extensive use of conventional morphological methods coupled with modern-day CNN-based feature extraction. While previous work, e.g., Zhang et al. [4], has shown the capability to extract vessels well with morphology-based approaches, integrating this with other image processing steps for improved diagnostic sensitivity with deep neural networks is unknown. In addition, although Xiaomeng Li et al. [3] proposed the Cross-Disease Consideration Network (CDCN) for real-time diagnosis of DR and DME, the method remains to be applied to other diabetic eye diseases such as glaucoma and cataracts. Constructing an integrated model that simultaneously diagnoses multiple diabetic eye diseases is a daunting and clinically valuable mission. In addition, most current lesion detection models depend either on learned or handcrafted features, and not much effort has been directed to systematically combining the two to enhance detection performance.

Another area significantly in need of more research is ensemble-based model building and its applications in reinforcing classification robustness on heterogeneous data. Work such as that by Zago et al. [7] has already demonstrated initial potential with ensemble CNNs. Still, a complete assessment of ensemble techniques across different classes of diseases and phases of disease must be undertaken. In addition, most of the models have been tested on small or homogeneous datasets, which are problematic for their use in real-life clinical practice with heterogeneous populations of patients and imaging environments. Proper deep learning-specific preprocessing pipelines need greater attention, especially optimizing routines like contrast normalization, resolution standardization, and data augmentation. Lastly, while AI technologies continue to become more mainstream for medical diagnosis, the explainability and interpretability of the models are of utmost concern for adoption in the clinic. Building explainable deep learning models that can provide explanations for predictions and provide visual insights into diagnostic judgment is of utmost concern to medical practitioner confidence and for safe, ethical application in clinical practice.

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III. METHODOLOGY

The suggested diabetic eye disease classification system aims to be high-performance, reliable, and adaptive. The end-to-end process, ranging from data collection and preprocessing to model training, evaluation, and deployment, is elaborated on in this section. The methodology is comprised of various significant stages.

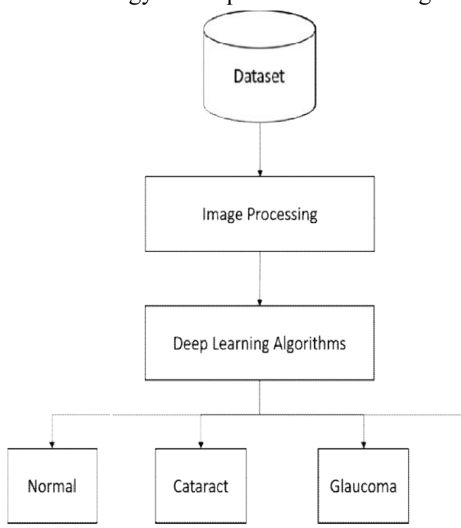

Figure 1: Block diagram of the proposed system

A. Input Dataset

The data used in this study is the cataract dataset, available online on Kaggle. The dataset consists of four different classes: normal, cataract, glaucoma, and retina disease, offering a complete picture of different diabetic eye diseases. For practical model training and testing, 75% of the dataset is assigned for training purposes, and the remaining 25% is kept for testing. This division strategy evaluates the generalization performance of the model on unknown data.

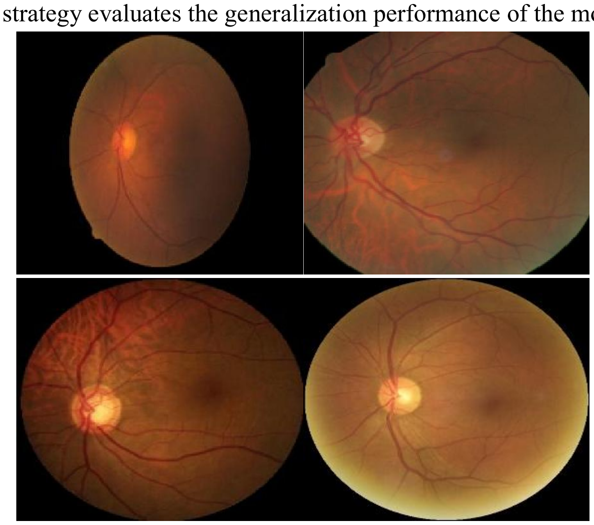

Figure 2: Sample images of the dataset

The distribution of the dataset is shown in Table I

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B. Dataset Distribution

	Total Image	Training Images	Testing Images
Cataract	1038	831	207
diabetic_retinopathy	1098	879	219
Glaucoma	1007	806	201
Normal	1074	859	215

C. Pre-processing

Before model training, the input images undergo a resizing operation to standardize their dimensions. Specifically, images are resized to a resolution of 256x256 pixels. This standardization facilitates consistency in input dimensions, ensuring compatibility with the chosen deep learning algorithms. Image quality enhancement techniques are applied to improve clarity and feature representation. These enhancements may include contrast adjustments, brightness normalization, or other preprocessing steps to optimize the input data for subsequent classification tasks.

Model Architecture Design.

Three deep learning architectures are selected, ensuring diverse performance evaluation: Convolutional Neural Network (CNN), Vgg19, and ResNet101.

Convolutional Neural Network (CNN): Convolutional Neural Networks (CNNs), a specialized type of neural network, is particularly effective for tasks like image recognition and classification. They belong to the category of multi-layered feed-forward neural networks. A CNN is composed of elements such as filters (also referred to as kernels or neurons), each having biases, learnable parameters, and weights. These filters process input data by performing convolution operations and can also apply non-linear functions as needed.

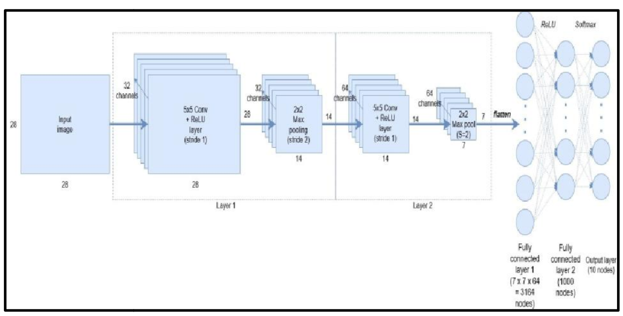

Figure 3: Block Diagram of CNN algorithm.

The custom CNN includes:

- Input Layer: Accepts 256x256 RGB images.
- Convolutional Layers: Extract features using 3x3 filters with ReLU activation for non-linearity.
- Pooling Layers: Max pooling (2x2) reduces dimensions while retaining key features.
- Fully Connected Layers: Flattens data and connects to dense layers for classification.
- Softmax Output: Outputs class probabilities for the four categories.

Vgg19 Architecture

Vgg19 Architecture is a deep Convolutional Neural Network (CNN) model with the reputation of being simple, having a uniform structure, and possessing high image classification performance. The Visual Geometry Group (VGG) of Oxford created this architecture. Vgg19 architecture is defined by usingtiny (3x3) convolutional filters with the same stride and padding in every layer. The Vgg19 algorithm architecture is presented in Fig.4.

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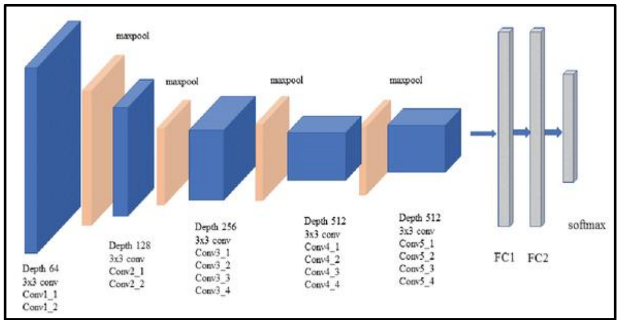

Figure 4: Architecture of Vgg19

Vgg19 contains 19 layers, 16 convolutional layers, and three fully connected layers, using small 3x3 filters. The network is modified to:

- Adapt the final dense layers to handle four classes.
- Integrate dropout layers to reduce overfitting.
- Use the Adam optimizer for faster convergence.

The structure comprises 19 weighted layers, of which 16 are convolutional and three are fully connected layers, thus making it deep and feature-extracting compared to previous CNN architectures. The blocks of convolution include a max-pooling layer after each block, reducing the spatial size and, therefore, reducing overfitting and computational cost. To apply Vgg19 for diabetic eye disease classification, it is modified to classify into four output classes: cataract, normal, glaucoma, and retina disease. Dropout layers are added between dense layers to avoid overfitting, and the Adam optimizer ensures successful convergence during training. Slow training of Vgg19 because of depth and successful hierarchical representation learning of retinal images are achieved. Its default natural ordering and transfer learning flexibility make it an excellent starting point model for such medical image-classifying issues as diabetic eye disease.

ResNet101 Architecture

ResNet101 Architecture is a convolutional neural network that tries to counteract the problem of training vigorous networks, such as vanishing gradients and decreasing accuracy. ResNet101 was developed as a member of the Residual Network (ResNet) family by Microsoft Research. ResNet101 has 101 layers and includes residual learning using shortcut (skip) connections. Shortcut connections skip one or more layers so that the network learns residual functions rather than direct mappings. The design facilitates the smooth propagation of the gradient in backpropagation so intense networks may be trained without being affected by their performance. The architecture diagram of the ResNet101 is represented in Fig.5.

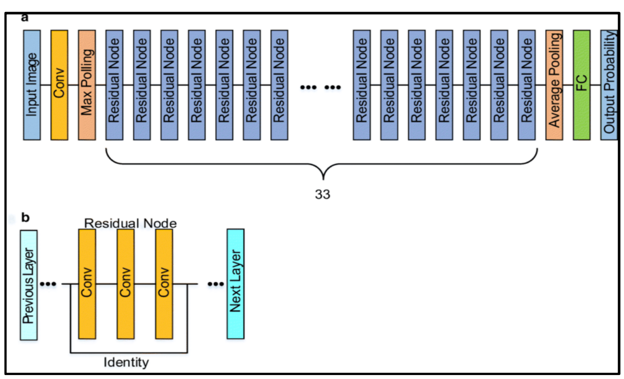

Figure 5: Architecture diagram of Resnet101 algorithm.

ResNet101 comprises residual blocks containing multiple convolutional layers, batch normalization, and ReLU activation functions. They have identity mappings, which add a layer's input to its output, effectively allowing the model to retain information from past layers and improve feature propagation. Within the classification of diabetic eye disease, ResNet101 comes in particularly handy to find hidden patterns from hard-to-calculate retinal images. The bottleneck nature, where the amount of parameters is minimized by employing 1x1 convolutions as before and after the employment of 3x3 convolutions, makes it hold depth without making computation cost expensive.

The model also replaces common dense layers with global average pooling, which removes overfitting and shrinks the model size, and then a Softmax layer in case of multi-class classification. ResNet101 yielded improved accuracy, precision, recall, and F1-score performance in the proposed system compared with shallower networks like CNN and Vgg19. It can extract meaningful deep features without overfitting, making it eligible for undertaking medical image classification tasks, particularly distinguishing between visually similar diabetic eye diseases.

D. Data Augmentation

To address data imbalance and improve generalization, augmentation techniques include:

- Rotation: ±15 degrees
- Zoom: ±10%
- Horizontal flip: Simulates different orientations
- Brightness adjustment: ±20%

This improves diversity, ensuring the model learns from various variations.

E. Performance Evaluation Metrics

The models are evaluated using key metrics to ensure reliability.

Accuracy: Measures overall correctness.

$$\text{Accuracy} = \frac{TP+TN}{TP+TN+FP+FN} \quad (1)$$

Precision: Reflects how many predicted positive cases are correct.

$$\text{Precision} = \frac{TP}{TP+FP} \quad (2)$$

Recall: Measures how many true positives are correctly identified.

$$\text{Recall} = \frac{.TP}{TP+FN} \quad (3)$$

F1-Score: Harmonic mean of precision and recall crucial for imbalanced datasets.

$$\text{F1 Score} = \frac{2\times(\text{Precision}\times\text{Recall})}{\text{Precision}+\text{Recall}} \quad (4)$$

IV. RESULTS AND DISCUSSION

The performance of the proposed system, leveraging CNN, Vgg19, and ResNet101 architectures, is evaluated using multiple metrics, including training accuracy, validation performance, classification reports, confusion matrices, and ROC curves. This section presents the results alongside corresponding diagrams, highlighting key insights from each model. The performance of each deep learning for classifying eye disease is shown below.

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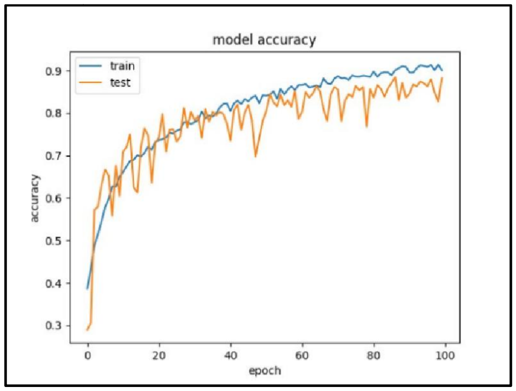
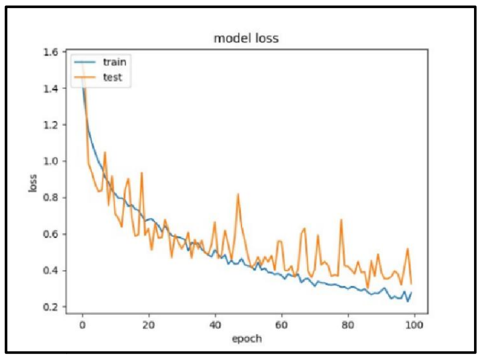
A. CNN algorithm



(a)

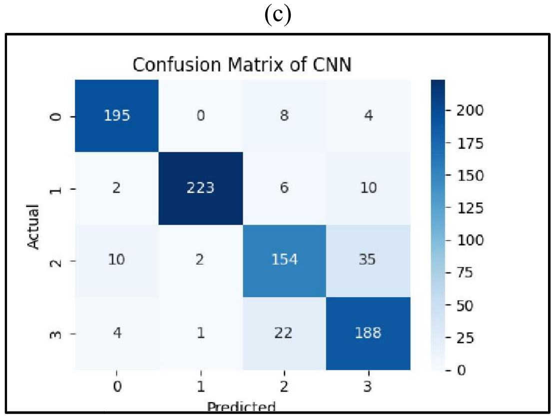


(b)

Classification Report

	precision	recall	f1-score	support
cataract	0.92	0.94	0.93	207
diabetic_retinopathy	0.99	0.93	0.96	241
glaucoma	0.81	0.77	0.79	201
normal	0.79	0.87	0.83	215
accuracy			0.88	864
macro avg	0.88	0.88	0.88	864
weighted avg	0.88	0.88	0.88	864

(c)



(d)

Figure 6: Performance of CNN algorithm (a) Accuracy (b) Loss (c) Classification report (d) Confusion Matrix

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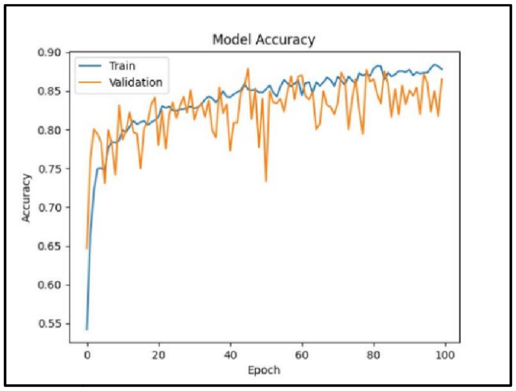
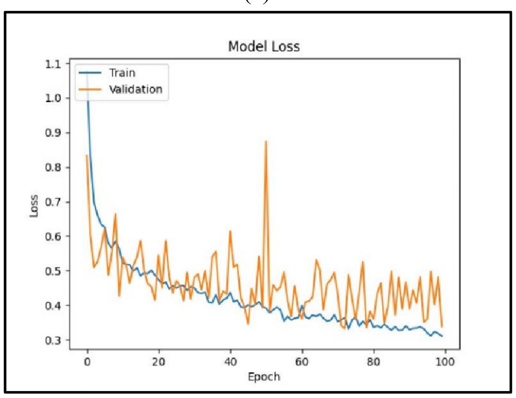
The CNN model showed an excellent learning ability with a training accuracy of 88.2%. However, its validation accuracy fell to 85.4%, a common overfitting issue. The model learned efficiently from the training set but could not generalize well to new samples. This is due to the relatively shallow structure of the CNN, which cannot extract complex features required in the differentiation of visually similar diseases such as glaucoma and cataracts. Although it has rapid convergence and easy architecture, CNN performed poorly in the clinical scenario because of lower recall values for underrepresented classes such as retinal diseases. The confusion matrix indicated misclassifications, implying that although CNN performs well in general pattern recognition, it does not have the depth needed for high-precision medical image classification tasks.

B. Vgg19 algorithm



(a)



(b)

Classification Report

	precision	recall	f1-score	support
cataract	0.86	0.96	0.91	207
diabetic_retinopathy	0.99	0.95	0.97	219
glaucoma	0.89	0.64	0.75	201
normal	0.76	0.90	0.83	215
accuracy			0.87	842
macro avg	0.87	0.86	0.86	842
weighted avg	0.87	0.87	0.86	842

(c)

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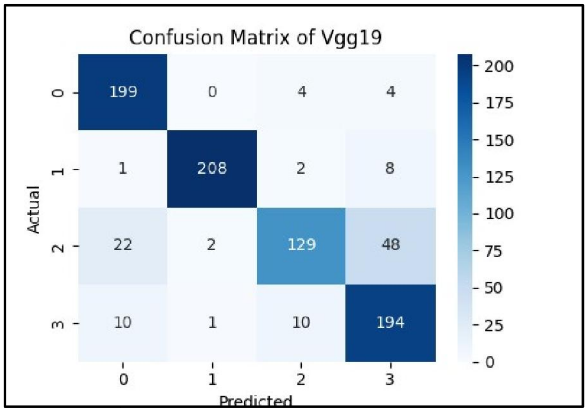
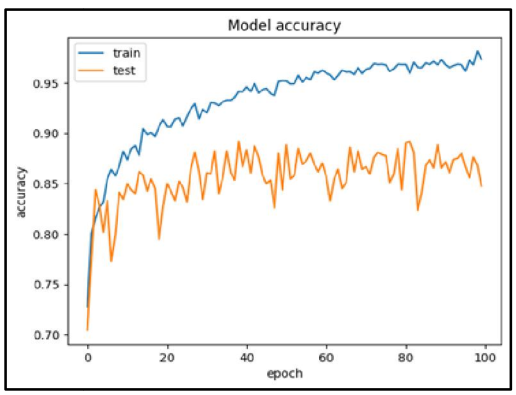


(d)

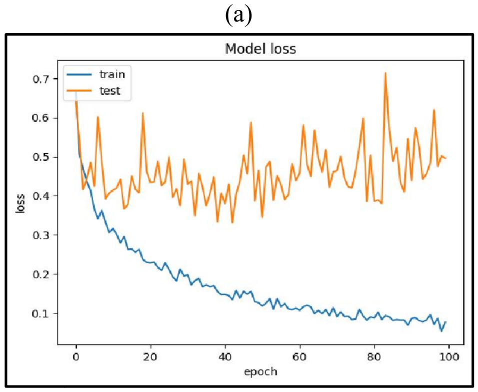
Figure 7: Performance of Vgg19 algorithm(a) Accuracy (b) Loss (c) Classification report (d) Confusion Matrix

Vgg19 did more evenly, with a validation accuracy of 86.3%. It generalized better than CNN because it had a deeper but more balanced structure that allowed it to learn hierarchical features. Although Vgg19 was beset by slow convergence because of its depth, it better identified unique patterns in retinal fundus images. However, its validity was compromised as it classified those illnesses based on comparable visual descriptions, sometimes mistakenly naming glaucoma and cataracts. The dropout layers could prevent overfitting, yet the training period and model complexity computationally remained high. Vgg19, in general, provided an acceptable classification benchmark and classified diabetic eye disease with sufficient accuracy, though not one hundred percent accurate,

Resnet101 algorithm



(a)

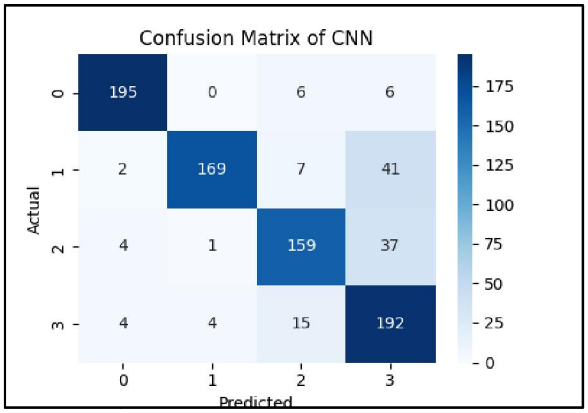


(b)

Classification Report

	precision	recall	f1-score	support
cataract	0.95	0.94	0.95	207
diabetic_retinopathy	0.97	0.77	0.86	219
glaucoma	0.85	0.79	0.82	201
normal	0.70	0.89	0.78	215
accuracy			0.85	842
macro avg	0.87	0.85	0.85	842
weighted avg	0.87	0.85	0.85	842

(c)



(d)

Figure 8: Performance of Resnet101 algorithm (a) Accuracy (b) Loss (c) Classification report (d) Confusion Matrix

ResNet101 performed the best overall, achieving 91.3% training accuracy and 89.5% validation accuracy. Its residual learning structure prevented it from experiencing vanishing gradients and sustaining performance at high depth. The model effectively extracted deep features, resulting in more precise classification, particularly in detecting subtle retinal abnormalities. The confusion matrix and classification report reflected fewer misclassifications and greater precision in all categories of diseases. Its steady low loss values and better recall made it suitable for clinical use. ResNet101 differed from CNN and Vgg19 in that it preserved depth and generalization. It thus proved to be the most reliable model in this research for robust and precise diabetic eye disease detection.

The comparative analysis of DL algorithms utilized for Eye disease recognition is shown in Table II.

Table 2: Comparative analysis of the performance of DL algorithms

Algorithm	***Training***		***Validation***	
	Accuracy	***Loss***	***Accuracy***	**Loss**
CNN	***0.88***	***0.88***	***0.88***	***0.88***
Vgg19	***0.87***	***0.87***	***0.86***	***0.87***
Resnet101	***0.87***	***0.85***	***0.85***	***0.85***

The comparative performance of CNN, Vgg19, and ResNet101 models reveals different patterns of training and validation. CNN model is excessively good at training at around 88.2%, whereas validation accuracy is low at 85.4%. This inconsistency indicates overfitting, i.e., where the model exaggerates learning training data, i.e., noise and outliers, but performs poorly on new unseen data. The performance is even less than ideal for clinical application, as the ability of the model to generalize to less typical cases or indeterminate cases—e.g., retinal disease, let us say, with fewer instances in the setcan be compromised by the result. The Vgg19 model, in turn, has enhanced imbalanced performance at 86.3% accuracy validation, with better generalization compared to CNN.

However, its stronger structure introduces the slow transition towards requiring longer epochs of convergence with the requirement to converge into a same-performance type of form. Also, since a similar look on a visual platform for conditions like cataracts and glaucoma is already present, the model sometimes mistakenly misinterprets common properties through the inability to recognize the finer granularity level. ResNet101 model, however, outperforms CNN and Vgg19 in terms of comprehensive performance metrics. It achieves a training accuracy of 91.3% and validation accuracy of 89.5%, showcasing its higher ability to learn deeper features without compromising generalization. Residual connections in its model improve the flow of gradients and minimize vanishing gradient problems, hence becoming more resistant to overfitting and applicable in real-world scenarios. ResNet101 is generally the most consistent and clinically helpful architecture.

It has the highest classifying precision, lowest loss values, and a low misclassifying rate of any of the classes, particularly performing very well at detecting mild retinal pathology. Although CNN learns incredibly quickly, it does not generalize to uncommon diseases. Vgg19 has a similar split, but computational complexity and slow training restrict its utilitarian efficiency. Overall, the capacity of ResNet101 to produce results and withstand different features in images makes it a highly viable candidate for clinical decision-making devices in the area of enhanced diagnostic sensitivity and dependability in the detection of diabetic eye disease.

V. CONCLUSION AND FUTURE SCOPE

The use of the deep learning models—CNN, Vgg19, and ResNet101—has proven AI-based diagnostic system potential for improving early detection and treatment of diabetic eye disease. The ResNet101 was the highest and most confident of the models tested, with more efficient performance and training accuracy and validation, precision, and recall. Its residual deep structure substantially succeeded in overcoming vanishing gradient issues and overfitting. It emerged firmly poised for extracting fine, subtle features crucial to differentiating between visually similar retinal diseases. While CNN and Vgg19performed well, training's generalization inefficiency was an issue in justifying more complex deeper networks like ResNet. Overall conclusions endorse that AI-assisted computer-based diagnostic systems may be helpful to clinical tools and enhance speed, efficiency, and uniformity of screening for diabetic eye disease, particularly in resource-scarce environments. In the future, the system can be improved by having large and inclusive datasets to advance model generalizability across environments and populations.

Future studies can also investigate applying attention mechanisms or ensemble models to improve classification performance and explainability. Implementing edge or mobile computing platforms like Raspberry Pi or NVIDIA Jetson would allow real-time point-of-care diagnosis in rural or underserved communities. Furthermore, improved explainability by heatmaps or saliency maps can lead to higher clinician trust. These developments will all propel the translation of this AI system from a research prototype to a scalable clinical tool for practical ophthalmologic applications.

REFERENCES

[1]. Wejdan L Alyoubi, Wafaa M Shalash and Maysoon F Abulkhair, "Diabetic retinopathy detection through deep learning techniques: A review," Informatics in medicine unlocked, 20, June 2020

[2]. Vijay Kumar Gurani, Abhishek R, Chiranji Lal C, "Diabetic retinopathy detection using neural network," International Journal of Innovative Technology and Exploring Engineering, 8(10), 2936-2940, Aug. 2019.

[3]. Xiaomeng Li; Xiaowei Hu; Lequan Yu, "CANet: Cross-Disease Attention Network for Joint Diabetic Retinopathy and Diabetic Macular Edema Grading," IEEE Transactions on Medical Imaging, Volume: 39, Issue: 5, 1483 – 1493, May 2020.

[4]. Lei Zhang, Qin Li, Jane You, David Zhang, "A Modified Matched Filter With Double-Sided Thresholding for Screening Proliferative Diabetic Retinopathy," IEEE Transactions on Information Technology in Biomedicine, Volume: 13, Issue: 4, 528 – 534, July 2009.

[5]. Sohini Roychowdhury, Dara D. Koozekanani, Keshab K. Parhi, "DREAM: Diabetic Retinopathy Analysis Using Machine Learning," IEEE Journal of Biomedical and Health Informatics, Volume: 18, Issue: 5, 1717 – 1728, Sept. 2014.

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[6]. S. M. S. Islam, M. M. Hasan, and S. Abdullah, "Deep learning based early detection and grading of diabetic retinopathy using retinal fundus images," Proc. Int. Conf. Mach. Learn. Image Process. Netw. Secure. Data Sci., Dec. 2018.

[7]. Zago. GT, Andreao. RV, Dorizz. B and Teatini Salles. EO, "Diabetic retinopathy detection using red lesion localization and convolutional neural networks. Computers in Biology and Medicine", 116, 103537, 2020.

[8]. Jiang. H, Yang. K, Gao. M, Zhang. D, Ma. H and Qian. W, "An interpretable ensemble deep learning model for diabetic retinopathy disease classification," 41st Annual International Conference of the IEEE Engineering in Medicine and Biology Society (EMBC), pp. 2045–2048, 2019.

[9]. Wang. X, Lu. Y, Wang. Y and Chen. WB, "Diabetic retinopathy stage classification using convolutional neural networks," International Conference on Information Reuse and Integration for Data Science, p. 465–71, 2018.

[10]. Pratt. H, Coenen. F, Broadbent. DM, Harding. SP and Zheng. Y, "Convolutional neural networks for diabetic retinopathy," Procedia Comput Sci., 90:200–5, 2016.

[11]. Abramoff. M. D, Lou. Y, Erginay. A, et al., "Improved Automated Detection of Diabetic Retinopathy on a Publicly Available Dataset through Integration of Deep Learning," Invest Ophthalmol Vis Sci., 57(13):5200-5206, 2016.

[12]. Mobeen-Ur-Rehman, Khan. S. H, Abbas. Z, Danish Rizvi. S. M, "Classification of diabetic retinopathy images based on customized CNN architecture," In: Proceedings-Amity International Conference on Artificial Intelligence, p. 244–8, 2019

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