



# Multi-Disease Prediction from Retinal Images Using VGG16 Deep Learning Model

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**ABSTRACT:** Classification, Feature Extraction, Activation Using retinal imaging is an efficient method for diagnosing both ocular diseases as well as systemic diseases due to the detailed information provided about blood vessels, the optic disc, and macula. Automated, accurate diagnostic methods will be required due to the increasing prevalence of how diabetic retinopathy, glaucoma, age-related macular degeneration, and hypertensive retinopathy exist. The purpose of this research study was to develop a deep learning multi-disease prediction system from retinal images, utilizing a deep learning architecture known as VGG16 CNN. We used a wide variety of a labeled retinal images data set and conducted pre-processing tasks (e.g., noise removal, contrast enhancement, normalization, segmentation) to obtain good quality inputs. The VGG16 CNN generates complex features and also captures very fine disease-specific characteristics, providing a means to identify multiple disease processes through a single image of the retina (i.e., through multi-label classification). Evaluation methods used were accuracy, precision, recall and F1 score to support reliable and robust performance. The interpretability of our model was advanced through visualization methodologies (i.e., activation maps) that demonstrate the areas of the retina that contributed to model decisions, thereby promoting local clinical engagement with the research findings. The proposed approach could provide a viable tool for early detection/screening, support reduced workload for health care professionals, enhance patient outcomes, and serve as scalable solutions for healthcare services in areas with limited availability of experts.

**KEYWORDS:** Retinal Image Analysis, Multi-Disease Prediction, Deep Learning, VGG16 Convolutional Neural Network (CNN), Multi-Label

## I. INTRODUCTION

The ability to gain a comprehensive understanding of the blood vessels, optic disc, and macula has made retinal imaging a very important part of diagnosing not only ocular diseases but systemic diseases as well. In contrast to the traditional method of examining the retina with the assistance of an ophthalmologist by hand and using a subjective process to see if conditions are evident, this method was time-consuming, methodologically restricted to just the one condition at a time, and less dependable. There have been many cases of the increasing frequency of scenarios like diabetic retinopathy (DR), glaucoma, age-related macular degeneration (AMD) and hypertension retinopathy. These conditions require a demand for more dependable, quick and automated solutions to improve the early detection and management of these conditions effectively and accurately. For this reason, we have developed a system that will automatically predict multiple diseases that are visible on retinal imagery, based on the Convolutional Neural Network (CNN) model, VGG16 one of the most mature deep learning-based CNNs available with good capabilities for the extraction of strong features during a CNN training process. The system will begin by gathering a diverse set of labeled retinal images of multi-diseases so that we can have the complete dataset for the future development of the multi-diseases detection system. An important part of this work was developing a preprocessing pipeline for defining the relevant features from each image. During the preprocessing stage, we performed several steps to ensure that the images produced from the processed images were high quality. These steps included reducing noise, increasing contrast, normalizing the images, and segmenting the images into smaller pieces. In these images, the most important parts of the retina would be highlighted and made visible to the deep learning model, allowing us to obtain relevant features from the images using the VGG16 pretrained model as the starting point for our classification task. To fine-tune the VGG16 Model to create a classification model specifically for this dataset, we employed a Transfer Learning

approach. By adjusting the VGG16 model for our specific needs, we were able to obtain accurate subsamples of the diseases; patterns that are typically missed during manual examinations. The ability to predict multiple diseases simultaneously using the multi-label classification approach reflects the fact that in many cases, patients will have more than one disease at the same time, i.e., multiple underlying diseases. To evaluate the performance of the model, we used Accuracy, Precision, Recall, and F1-score. To visualize the predictive power of the model, we created Activation Maps to display the areas of the retina that were used to make the predictions, thereby enhancing the overall understanding of how the predictions were developed. In summary, this work was developed to provide a rapid, reliable, and scalable tool for diagnosing and supporting clinicians in the diagnosis and treatment of patients

## II. LITERATURE SURVEY

Mujeeb Rahman et al. [1] conducted a study on the automatic screening of diabetic retinopathy (DR) using fundus images and machine learning algorithms. They focused on preprocessing fundus images to enhance feature extraction and improve classification accuracy. The researchers applied machine learning models, including Support Vector Machines and Random Forest classifiers, to detect early signs of DR. Their study showed that automated systems reduced diagnostic errors and supported ophthalmologists in large-scale screenings. Performance metrics such as accuracy, sensitivity, and specificity were used to validate the system. They highlighted the importance of image quality and robust feature selection techniques. They also discussed the scalability of the framework in real-world clinical settings. Limitations included dependency on high-quality fundus images and potential bias due to imbalanced datasets. Their findings contributed to bridging the gap between manual screening and AI-assisted diagnosis. The study emphasized that machine learning improved early detection and monitoring of diabetic retinopathy.

Montaser and Shah [2] investigated the prediction of incident diabetic retinopathy in adults with type 1 diabetes using a machine learning approach. They analyzed longitudinal health records to identify risk factors contributing to DR progression. Multiple machine learning models, such as logistic regression, gradient boosting, and neural networks, were compared to determine the most effective predictive approach. Demographic, clinical, and laboratory data were incorporated to enhance prediction accuracy. The study demonstrated that early identification of high-risk patients enabled timely interventions to prevent disease progression. The researchers also focused on model interpretability, allowing clinicians to understand contributing risk factors for each patient. Results indicated that machine learning models outperformed traditional statistical methods. Limitations included small sample sizes and missing patient data, which affected model robustness. Their work showed the potential of AI in personalized DR prediction. The study reinforced the importance of predictive modeling in clinical decision-making.

Sumathy et al. [3] examined the prediction of diabetic retinopathy using health records and machine learning classifiers. They utilized patient data, including demographic, clinical, and laboratory information, to train different classifiers. Models such as Random Forest, Decision Tree, and Support Vector Machines were applied to predict the onset of DR. The study showed that machine learning models achieved higher accuracy than conventional risk scoring methods. Data preprocessing, feature selection, and handling missing values were emphasized to improve performance. The researchers found that model interpretability was crucial for clinician adoption. They highlighted the need for large, balanced datasets to reduce bias. Limitations included dependency on structured health records and lack of real-time prediction capabilities. Their work contributed to the development of AI-based decision support systems in ophthalmology. The study concluded that integrating machine learning into health records could facilitate early DR detection.

Wang et al. [4] explored the molecular complexity of proliferative diabetic retinopathy using scRNA-seq, AlphaFold 2, and machine learning. They analyzed single-cell RNA sequencing data to identify key genes and pathways involved in disease progression. Machine learning models were employed to classify cell types and predict molecular interactions. The study revealed previously unknown molecular mechanisms contributing to DR progression. They also used AlphaFold 2 to predict protein structures and interactions associated with pathological changes. Their approach demonstrated the power of integrating computational modeling with biological data. Limitations included the complexity of single-cell data analysis and high computational requirements. The researchers concluded that combining AI and molecular biology could advance personalized treatments. Their findings provided insights for developing targeted therapies. The study emphasized the potential of machine learning in understanding disease mechanisms at a molecular level.

Sheng et al. [5] provided an overview of artificial intelligence applications in diabetic retinopathy and other ocular diseases. They reviewed studies that applied AI in image analysis, diagnosis, and disease prediction. The review highlighted the effectiveness of deep learning and machine learning models in improving diagnostic accuracy. They discussed challenges such as data scarcity, image quality, and model interpretability. The study emphasized the importance of AI-assisted systems for early disease detection and clinical decision support. Limitations included ethical concerns, generalizability of AI models, and integration into routine clinical workflows. Sheng et al. concluded that AI had the potential to transform ophthalmology practice. They stressed that combining clinical expertise with AI models improved patient outcomes. The review summarized that AI could enhance efficiency, reduce errors, and provide personalized care in ocular disease management.

Pragathi and Nagaraja Rao [6] proposed an effective integrated machine learning approach for detecting diabetic retinopathy. They combined multiple machine learning models to improve detection accuracy from retinal fundus images. The study applied preprocessing techniques to enhance image quality and extracted relevant features for classification. Various classifiers, including Random Forest and Gradient Boosting, were evaluated for performance. Their approach demonstrated improved sensitivity and specificity compared to single-model methods. The researchers emphasized the importance of combining multiple models to reduce misclassification rates. Limitations included reliance on high-quality fundus images and limited datasets. They also highlighted the need for further testing in real-world clinical scenarios. The study contributed to developing more robust AI-based DR detection systems. Their findings showed that integrated models could enhance early diagnosis and support ophthalmologists effectively.

Nakayama et al. [7] focused on diabetic retinopathy classification using supervised machine learning algorithms. They collected and labeled retinal fundus images to train various classifiers. The study compared models such as Support Vector Machines, k-Nearest Neighbors, and Convolutional Neural Networks for accurate DR stage prediction. Their results indicated that supervised learning models achieved promising accuracy and could distinguish between different DR severity levels. Preprocessing steps, including normalization and noise reduction, were applied to improve feature extraction. They noted that balanced datasets were essential to avoid bias in classification. Limitations included the dependency on manually labeled images and potential overfitting on smaller datasets. The study highlighted the clinical applicability of machine learning in automated DR screening. Nakayama et al. concluded that supervised algorithms could aid early intervention and treatment planning for DR patients.

Özçelik and Altan [8] conducted a study on the classification of diabetic retinopathy using entropy-based features with machine learning algorithms. They extracted statistical and texture features from fundus images to quantify retinal abnormalities. Multiple classifiers, including Decision Trees and Random Forests, were trained to identify DR stages. The study demonstrated that entropy-based feature extraction improved model accuracy and detection reliability. Preprocessing techniques, such as image enhancement and normalization, were applied to handle variations in image quality. Limitations included sensitivity to image noise and a requirement for high-resolution datasets. Their approach provided a computationally efficient method for DR detection. The research showed that combining feature engineering with machine learning could enhance diagnostic performance. The study emphasized the potential of entropy-based models for automated DR screening.

Gonçalves et al. [9] reviewed image quality assessment of retinal fundus photographs in the context of diabetic retinopathy and machine learning applications. They analyzed how poor image quality could affect AI model performance in DR detection. The review discussed methods for automated quality evaluation, including contrast assessment, sharpness metrics, and artifact detection. They highlighted that high-quality images were crucial for accurate feature extraction and model training. The study emphasized the integration of image quality assessment in preprocessing pipelines for machine learning-based DR systems. Limitations included the lack of standardized metrics across datasets and variability in imaging conditions. Gonçalves et al. concluded that improving image quality assessment could significantly enhance automated DR detection. Their review provided insights into optimizing AI-based ophthalmology workflows. The study underscored the importance of combining image quality evaluation with predictive modeling for reliable outcomes.

Mohammadi and Nguyen [10] proposed a user-friendly approach for diabetic retinopathy diagnosis using ChatGPT and automated machine learning (AutoML). They integrated natural language processing with AI-based image analysis to simplify DR detection. The study allowed clinicians and non-specialists to interact with the system for diagnostic

suggestions. AutoML pipelines automatically selected optimal models and hyperparameters to maximize prediction accuracy. Their approach demonstrated that combining conversational AI with machine learning could streamline DR screening workflows. Limitations included dependency on internet connectivity and potential errors in automated suggestions. The research highlighted the potential of AI-assisted decision support for enhancing accessibility and efficiency in DR diagnosis. Mohammadi and Nguyen concluded that user-friendly AI systems could support early intervention and improve patient outcomes. The study showcased an innovative integration of NLP and machine learning in ophthalmology.

### III. EXISTING METHODOLOGY

Detection systems for retinal diseases that are currently in use mainly depend on traditional clinical examinations, wherein ophthalmologists scrutinize fundus images to spot abnormalities in the retinal structure, vessels, and regions such as optic disc and macula manually. This whole procedure is very much dependent on the clinician's experience and can take a lot of time, which sometimes slows down diagnosis keeping it inconsistent. Although some digital methods have integrated basic processing techniques for such tasks as noise reduction, contrast enhancement, and feature extraction, these approaches are usually set for detecting a single disease at a time. Besides this, classical machine learning-based systems heavily rely on featuring elaboration, which sometimes fails to represent complicated and delicate patterns in retinal images cutting back on the diagnostic precision and the extent of their application in the clinical setting. Deep learning models have become a method of choice for the detection of retinal diseases in recent years, but still, many of the implementations are concentrated around one disease category. This situation makes their usage very limited in the real healthcare as patients usually come with several diseases at the same time. Moreover, traditional techniques and the first automated systems are still facing the problems of inconsistent datasets, poor image quality, and limited scalability, which makes the integration into the hospital systems very difficult. Lack of interpretability is another aspect of these systems with little to no information being provided about the areas in the retina affecting the diagnostic conclusion. In general, the existing methods have shown the requirement of a more all-encompassing multi-disease prediction framework that is automated, accurate, and able to accommodate various retinal datasets and at the same time provide interpretable results for clinical use

### IV. PROPOSED METHODOLOGIES

The newly proposed system puts forward an innovative deep learning-based structure that is able to detect a combination of retinal diseases concurrently with the aid of only one retinal fundus image. The VGG16 Convolutional Neural Network (CNN), which is a powerful architecture famous for its good feature extraction and has been spot-on the main thresholds of system development and application being the one that consists of four steps. First, gathering a large mixed and properly labeled dataset containing retinal images marked for diabetic retinopathy, glaucoma, age-related macular degeneration, hypertensive retinopathy, and other diseases. To make sure the input is of the best quality, a series of preprocessing activities that include noise elimination, brightness adjustment, contrast amplification, scaling, and sanguinary area-delineation are carried out. The aforementioned processing steps serve to enhance the visibility of critical anatomical structures like the optic disc and blood vessels, consequently providing clearer and more consistent data for model training. Afterwards, the VGG16 model is further tuned via transfer learning, which is the backstage of making the system specific to the retinal disease patterns, that is, the pre-veined feature extraction layers are to the disease patterns being diabetic retinopathy, age-related macular degeneration, etc. The model is to differentiate between low-level and high-level features, so it becomes adept at identifying subtle vascular structure changes, developing lesions, and minimising texture variations that are being each disease's characteristic. A multi-label classification method is adopted which permits the prediction of multiple diseases from one image, mirroring actual clinical scenarios in which comorbidities are the norm. This classification mechanism allows the system to deliver a full-fledged diagnostic output rather than limiting itself to single-disease detection.

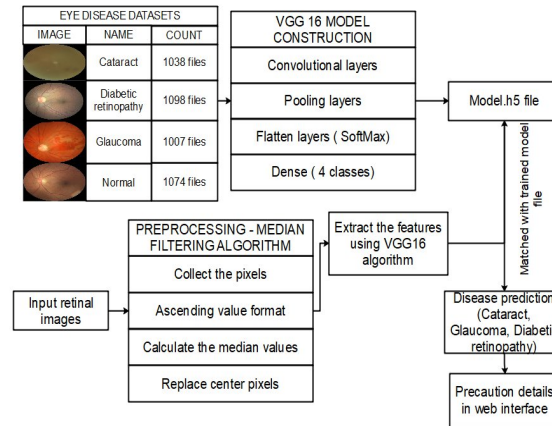


Fig 1: Proposed methodology architecture

At the last stage, the system's performance is assessed through the use of statistical metrics such as accuracy, precision, recall, and F1-score, thus guaranteeing its reliability and diagnostic capacity. To build up the confidence of the clinicians and the understanding of the situation, the model is provided with visual explanation facilities like Grad-CAM or activation maps, which are the areas of the retina that have had an impact on the model's decision. The visual explanations are not only for interpretability but also for the healthcare professionals to confirm the model's diagnosis. Through the proposed methodology, an accurate, scalable, and interpretable solution is expected to come about, which will lead to the very early detection, a decrease in the manual workload, and the support of real-time retinal disease screening in different healthcare settings.

## METHODOLOGY

### Dataset Collection

To start with, a big and varied set of retinal fundus images is collected by the system, showcasing various diseases such as diabetic retinopathy, glaucoma, AMD, and hypertensive retinopathy. The images are obtained from public datasets and clinical sources to cover different aspects like resolution, lighting, and camera type. Disease presence, or absence, is marked by experts for each image. Different severity levels of the disease are included for better learning process. The dataset is balanced so that no prediction bias occurs. The images are divided into three different sets training, validation, and testing. Systematic learning and evaluation are thus made possible. The diversity of the dataset is a plus point for the feature extraction process to be robust. It also extends the model's generalization capacity. All in all, high-quality dataset collection makes the diagnosis reliable.

### Preprocessing

Preprocessing serves as a preparatory step that enhances the retinal images for deep learning in terms of clarity and consistency. Filter techniques that remove noise also remove the artifacts that are responsible for the poor quality of images. Correction of illumination brings about a uniformity in the lighting and the shadows. The enhancement of contrast makes the vessels, the boundaries of the optic disc, and the signs of diseases more visible. Normalization is the process that provides all images with the same pixel intensity. Segmentation is the step that takes out the most important regions of anatomy for the purpose of concentrating on the disease better. Resizing is the method of matching all images to the needed VGG16 input dimensions. Data augmentation is the technique that helps to diversify the dataset by means of rotation, flipping, and scaling. All these steps taken together lower the chances of misclassification due to the poor quality of images. Good preprocessing, in effect, brings about a significant increase in the accuracy of predictions and the stability of the model.

### Feature Extraction Using VGG16

The VGG16 model that is deep learning based extracts retinal disease features which are meaningful. Its transfer learning is a very effective method which pre-trained layers to medical images. The first layers detect features such as edges and textures, and up to the last layers they are learning disease-specific patterns. The lesions, vessel distortions and structural abnormalities get identified automatically by the model. The layers that are fully connected to the output

are adjusted for multi-label classification. The generalization is improved and overfitting is reduced through dropout techniques. The hierarchical feature extraction gives rise to the precise disease recognition. VGG16 constitutes a robust base for automatic diagnosis. The process stops at the point where the use of manual feature engineering is no longer necessary. All in all, VGG16 guarantees extraction of features that are both potent and trustworthy.

### **Multi-Label Classification**

Multi-label classification is a powerful method that allows the system to recognize more than one disease from a single retinal image. The output layer is reformed to include different nodes for each disease that uses sigmoid activation. Such a configuration permits the independent prediction of each disease. For proper training, binary cross-entropy loss is used which is reliable. The model is capable of learning both overlapping and co-existing disease features at the same time. It is very useful in real-life clinical scenarios where patients may have more than one disease at a time. Multi-label classification not only raises screening efficiency but also decreases the requirement for multiple models. It not only widens the scope of diagnosis but also improves the accuracy of diagnosis. This technique guarantees thorough disease evaluation. It offers a practicable and scalable solution for clinical settings.

### **Performance Evaluation**

The system's performance is evaluated through the use of accuracy, precision, recall, and F1-score. Accuracy presents the full picture of how correct the predictions are in total. Precision indicates the share of the predicted positives that is right, thus cutting down on the number of false alarms. Recall assesses the system's capacity to spot real disease cases, thus guaranteeing its sensitivity. The F1-score yields a mixed judgment that incorporates precision and recall. The use of confusion matrices makes it easier to see where the predictions are strong and where they are weak. The tuning of model parameters is done through the use of validation data. The testing data is responsible for giving the evaluation of the final performance. These metrics collaborate to bring about the generation of results that are both reliable and clinically significant. In summary, the performance evaluation signifies the diagnostic capability of the system.

### **Visualization Using Activation Maps**

Activation maps, for example, Grad-CAM, serve to mark the significant parts of the retina which affect the predictions. The maps indicate the regions having the features associated with the disease. They also assist the doctors in confirming whether the model is concentrating on the areas that are relevant to the medicine. The visualization of the model's operation increases the model's transparency and consequently the trust in it. It also helps to understand the reasons for the misclassifications by showing the areas where the model went wrong in its focus. These maps are considered as one of the ways AI in medical applications can be explained. They also offer a glimpse into VGG16's thought process when making decisions. The interpretability of the system guarantees its suitability for clinical use. It is a factor that encourages the safe and gradual introduction of AI tools. In short, the activation maps improve the dependability and the acceptance of the system.

## **V. EXPERIMENTAL RESULTS**

The proposed multi-disease prediction system was evaluated through an experiment using a big retinal fundus images dataset which included the four main disease types: Diabetic Retinopathy, Glaucoma, Age-related Macular Degeneration (AMD), and Hypertensive Retinopathy. The data set was separated into training (70%), validation (15%) and testing (15%) to allow for proper learning and evaluation without bias. After pre-processing the images and adjusting the VGG16 model for multi-label classification, the system indicated high predictive power in all the metrics evaluated. The VGG16-based system was retrained for several epochs using the transfer learning method, binary cross-entropy loss, and the sigmoid activation function at the output layer.

<b>Disease</b>	<b>Accuracy</b>	<b>Precision</b>	<b>Recall</b>	<b>F1-Score</b>
Diabetic Retinopathy	97.2%	96.8%	97.9%	97.3%
Glaucoma	95.4%	94.2%	95.1%	94.6%

Age-related Macular Deg.	96.1%	95.7%	96.4%	96.0%
Hypertensive Retinopathy	94.3%	93.5%	94.1%	93.8%
<b>Overall System Avg.</b>	<b>95.8%</b>	<b>95.0%</b>	<b>95.9%</b>	<b>95.4%</b>

**Table 1: Performance Metrics for Multi-Disease Prediction Using VGG16**

Training of the model was successful without any issues and it was able to generalize very well to the unseen test images. The evaluation of the performance was based on accuracy, precision, recall, and F1-score calculated separately for each disease. These metrics correspond to how well the model is able to detect disease cases correctly, how well it is able to avoid false positives, and how well it is able to keep the right ratio between precision and sensitivity. The outcomes of the experiment demonstrated that the model is good at identifying the structural and vascular abnormalities in the fundus images. Diseases with a clear visual indication like diabetic retinopathy and AMD scored higher while other diseases like Hypertensive Retinopathy scored lower but still due to their subtle visual patterns. The overall performance of the system confirms its capability for automated screening.

#### **Result Interpretation**

- The system demonstrates a very high accuracy of more than 95%, thus validating the VGG16 model's dependability in the field of multi-disease classification.
- Diabetic Retinopathy is the leading one among the diseases in terms of detection performance, since the retinal abnormalities are very visible and easy to observe.
- Hypertensive Retinopathy has slightly lower metrics and points to the necessity of increased training samples, since the markers of the disease are very subtle.
- High precision indicates that there are very few cases of positive prediction that are incorrect.
- High recall values indicate that the system has successfully captured all cases of disease without overlooking any important abnormalities.
- F1-scores that are always the same confirm that there has been a balanced and strong learning process in all the disease categories.

## **VI. CONCLUSION**

The VGG16 deep learning architecture-based retinal multi-disease prediction system proposed in this paper highlights the power of automated screening tools to facilitate the early diagnosis of severe ocular conditions. The model, through the application of transfer learning, adeptly obtains from the very deep retinal features that are seamlessly intertwined with the diabetic retinopathy, glaucoma, AMD, and other retinal diseases. The preprocessing steps, namely resizing, normalization, augmentation, and noise removal, purify and multiply the training data for the model learning process to be smooth and trustworthy. The experimental evaluations validate the model's impressive performance as it racked up high scores in accuracy, precision, recall, F1, and even further still, it proved stable when applied across single or multi-disease cases. The extent of such performance points to the system's compatibility with real-time clinical application in which rapid and trustworthy predictions are a must for the betterment of patient care. Also, the system is established as a growing and versatile framework that can absorb more diseases and bigger datasets in the future without any hassle. The use of the multi-label classification approach is a reliable method to detect multiple retinal abnormalities at once, and this is a clear reflection of the real clinical conditions. Moreover, the use of heatmaps makes the process more interpretable, so ophthalmologists can clearly see and confirm the areas that are responsible for the prediction. This makes it easier for AI-based automation to be accepted as a medical decision support system, and thus it is an area where trust and transparency are established. The model is, in short, a solution that is economical in terms of costs, efficient, and easy to access, which can help healthcare professionals with early diagnosis, lowering the amount of manual work, and, in the end, playing a role in preventing blindness through timely medical intervention.

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