Detection of Ocular disease using Transfer and Federated Learning

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***Abstract*—In the current era, the widespread adoption of Transfer and Federated Learning techniques has revolutionized healthcare disease detection, driving remarkable innovation to new frontiers, notably transforming the detection of ocular diseases into a breakthrough. This research explores the efficacy of these methods in leveraging shared knowledge from diverse datasets while preserving data privacy. Transfer Learning enables the transfer of knowledge gained from one domain to another, enhancing the training of ocular disease detection models. Federated Learning further enhances this by allowing collaborative model training across multiple decentralized data sources without centralizing sensitive information. This research shows the application of Transfer and Federated Learning for Ocular Disease Detection. Leveraging the ODIR dataset. The study highlights EfficientNetV2's exceptional accuracy of 78.12%, surpassing its predecessors and demonstrating superior performance in ocular disease detection, despite increased computational time. Furthermore, the study delves into incorporating Federated Learning, ensuring security and privacy in collaborative model training across decentralized healthcare settings, while addressing challenges and considerations regarding the implementation of these advanced methods in ocular disease detection, encompassing privacy and ethical considerations.**

***Index Terms*—Ocular Disease Prediction, EfficientNetV2, Federated Learning, Diabetes, Cataract, Glaucoma**

I. Introduction

A. Motivation

Ocular diseases encompass a spectrum of conditions affecting the eyes, ranging from common refractive errors to severe disorders impacting vision and eye health. Detecting ocular diseases involves the identification and assessment of various eye conditions using specialized diagnostic tools, imaging techniques, and advanced technologies to ensure accurate identification and prompt treatment. The motivation behind employing Transfer and Federated Learning for ocular disease detection is to revolutionize how eye conditions are diagnosed. In many regions, access to specialized eye care is limited. By utilizing these advanced learning methods, the goal is to create models that learn from existing data (Transfer Learning) and collaborate without sharing sensitive information (Federated Learning). This enables more accurate diagnoses while respecting patient privacy—a crucial concern in healthcare. The overarching aim is to empower healthcare providers with enhanced diagnostic tools that can be deployed widely, ensuring better eye care for diverse populations, regardless of geographical constraints, and maintaining the confidentiality of patients' health data.

B. Problem Statement

Detecting ocular diseases such as glaucoma, diabetic retinopathy, and cataracts early on through early fundus screening is crucial for preventing irreversible blindness and preserving overall eye health. These diseases often develop gradually. Regular eye screenings are crucial because these diseases may not show noticeable symptoms during their initial phases. Glaucoma, for instance, is often referred to as the "silent thief of sight" because it progresses without obvious warning signs until significant vision loss occurs. Similarly, diabetic retinopathy, a complication of diabetes, can advance without clear symptoms, affecting the blood vessels within the eye's retina and leading to irreversible vision impairment. Cataracts, although treatable with surgery, can impair vision if left unattended. Early detection enables timely intervention and management, allowing healthcare professionals to implement appropriate treatments and lifestyle adjustments. Regular eye check-ups not only facilitate the identification of these conditions but also contribute to the prevention of blindness, ensuring individuals can maintain their visual acuity and quality of life.

While deep learning proves effective in image-based recognition, optimal performance relies on abundant labelled data. However, collecting and annotating large amounts of ocular disease data can be time-consuming, error-prone, and complicated. Acquiring multi-site data introduces challenges related to data privacy and domain gaps among sites, potentially compromising recognition performance.

C. Objectives and Contribution

In this study, our goal is to establish an innovative machine-learning model that significantly enhances the accuracy of ocular disorder detection compared to existing methods. Through the utilization of federated learning, we aim to build a model that surpasses existing methods in predicting optic disorders more efficiently. The key contributions of our study are as follows:

- Analysis of the existing methodologies and techniques used for identifying optical diseases.
- Trained several individual classification models for optic disease prediction.
- Implementation of federated learning implementation .

D. Research Structure

The remaining sections of our paper are structured as follows: Section II contains summaries of related work and background studies on various models. Section III provides an overview of our datasets. Moving on to Section IV, we present the details and description of our proposed method. Section V discusses the results and analysis of our proposed system. Finally, Section VI concludes the paper and outlines future works.

II. Related Works and Background

A. Related Works

This study [2] introduces an approach based on deep learning diagnosis of ocular diseases. The research employed advanced image categorisation algorithms, including VGG-19, to examine the ODIR dataset, which consists of 5000 retinal images classified into eight distinct classes representing different ocular diseases. However, the dataset exhibited significant imbalance among these classes. To address this inequality, the authors recommended transforming the multiclass classification challenge into a binary classification task to ensure an equitable distribution of images among each category. Following this, VGG-19 underwent training based on the binary classifications. The performance of the VGG-19 model demonstrated an accuracy of 98.13% in distinguishing between normal and pathological myopia, 94.03% for differentiating normal and cataract cases, and 90.94% for detecting normal and glaucoma cases. Notably, balancing data enhanced the accuracy of all models.

In order to offer a reliable and cost-effective means for early diagnosis of ocular diseases that impact an individual's eye health the researchers [3] of this study propose a system based on deep learning. They employed the Ocular Disease Intelligent Recognition (ODIR) dataset with annotations performed by trained human readers to ensure accuracy and eliminate mislabeled data. Leveraging computer vision and deep learning, the model demonstrates proficiency in detecting abnormalities from high-resolution fundus images. The proposed model undergoes testing with diverse disease combinations, achieving a peak accuracy of 93% for individual diseases and an accuracy of 83% for multiple diseases.

In the pursuit of precise detection of ocular tumors, the authors in [4] research introduced four deep learning-driven models. While conducting their study, they employed cutting-edge image categorization algorithms, including MobileNetV2, Resnet-34, VGG-16, and EfficientNet which underwent training on the ODIR dataset containing 5000 fundus images distributed across 8 distinct categories representing different ocular diseases. The VGG-16 model demonstrated an accuracy rate of 97.23%, Resnet-34 achieved 90.85% accuracy, MobileNetV2 exhibited an accuracy of 94.32%, and the EfficientNet classification model attained 93.82% accuracy. These models are positioned to play a vital function in the development of a system capable of promptly diagnosing ocular diseases.

The authors from [5] study introduces an innovative multi-label convolutional neural network framework based on multi-label classification for the identification of diverse ocular diseases in color fundus images. The proposed system encompasses three primary phases: a preprocessing stage involving normalization and augmentation through various transformation processes, a modeling phase, and a prediction phase. The ML-CNN architecture comprises three convolution layers and a single max pooling layer. Subsequently, two convolution layers are executed, succeeded by one MP layer and dropout. Following this, a flatten layer is applied, succeeded by a fully connected layer. Another instance of dropout is introduced, concluding with a fully connected layer featuring 45 nodes. The system generates likelihood scores for all 45 diseases in each image. To assess model reliability, cross-validation is employed, and performance is gauged using five metrics: recall, accuracy, Dice similarity coefficient, precision, and area under the curve (AUC), yielding respective results of 80%, 94.3%, 99%,91.5%, and 96.7%. A comparative examination with established models such as SeResNext50, DenseNet201, MobileNetV2, InceptionV3, and InceptionresNetv2 highlights the superior performance of the suggested ML-CNN architecture.

The research paper [6] is centered on the early detection of Eye conditions identified through retinal fundus images obtained from an internet-based dataset. These images underwent preprocessing through maximum entropy transformation. A CNN is employed for feature extraction, optimized with a flower pollination optimization algorithm. The optimization algorithm was also utilized to optimize hyperparameters during CNN training, enhancing both speed and accuracy. The output of the CNN is subsequently fed into a Multiclass Support Vector Machine classifier for categorizing the type of disease. The suggested CNN-based method for detecting multiple diseases is evaluated using the Ocular Disease Intelligent Recognition dataset.Upon comparison with other optimized models, the presented model demonstrates exceptional performance metrics. It achieves a high accuracy of 95.27%, precision of 98.30%, recall of 93.3%, specificity of 95.21%, and an impressive F1 score.

B. Background

1) Ocular diseases and Fundus: Ocular diseases refer to a wide range of conditions that affect the eyes.The fundus, referred to as the ocular fundus or the fundus of the eye, constitutes the inner surface of the eye positioned opposite the lens. It encompasses the macula, retina, optic disc, and blood vessels.Examination of the fundus is a crucial aspect of eye care, and it can provide valuable information about the overall health of the eyes and the presence of various ocular diseases.Here are some key ocular diseases and their association with the fundus:

- Glaucoma comprises a set of eye conditions causing damage to the optic nerve, frequently associated with elevated intraocular pressure. This condition can result in vision loss and eventual blindness.
- Cataracts develop when the eye's lens becomes cloudy, leading to blurry vision. Although aging is a frequent contributor, diabetes can accelerate the advancement of cataracts.
- Diabetic retinopathy, a diabetes complication, impacts the blood vessels within the retina and stands as a primary cause of blindness among adults.

Regular eye exams are crucial for detecting and managing these conditions early. Diabetic patients should have regular screenings for diabetic retinopathy, while routine eye checkups are essential for identifying cataracts and glaucoma. Timely intervention can help in managing these ocular diseases effectively and preserving vision.

2) EfficientNetV2 Architecture: EfficientNetV2 represents a progression from EfficientNet in 2021 [1]. It increases training speed and parameter efficiency. It's crafted by combining scaling factors (width, depth, resolution) and neural architecture search. This iteration introduces novel convolutional blocks Fused-MBConv to enhance its architecture. Fused-MBConv blocks, combining MBConv and simpler 3x3 convolutions, aimed to utilize accelerators more efficiently. EfficientNetV2 demonstrated that well-structured CNN models with enhanced training methods can outperform transformers in speed and accuracy, asserting the continued relevance and effectiveness of CNNs in computer vision. EfficientNetV2B1 comprises approximately 7 million parameters.

3) Transfer Learning: Transfer learning is a machine learning strategy that involves utilizing a model previously trained on one task to enhance performance on a different yet related task. Instead of initiating training for a specific task from the ground up, transfer learning utilizes the existing knowledge and features of a pre-trained model as a foundational starting point. The early layers, capturing general features, are retained, while later layers are adjusted for the specific task through fine-tuning. This method harnesses knowledge from a source task to enhance performance on a related target task, proving especially valuable when there is a scarcity of labeled data for the target task. The concept is that the insights acquired from solving one task can be transferred to a new, similar task, potentially minimizing the need for extensive labeled data and reducing the training time required for the new task. Transfer learning demonstrates notable efficacy in deep learning scenarios, where models involve numerous layers and parameters.

4) Federated Learning: Federated learning revolutionizes machine learning by adopting a decentralized model training paradigm. Instead of centralizing data on a server, federated learning allows model training to occur locally on individual devices. This innovative approach preserves privacy as raw data remains on the edge devices. Model updates are then shared with a central server, facilitating collaborative learning across distributed networks. Particularly beneficial in privacy-sensitive domains, such as healthcare and finance, federated learning ensures data security while enabling continuous model improvement.

III. Dataset Description

In this research, we utilized the ODIR-2019 (Ocular Disease Intelligent Recognition) dataset, which stands out as an extensive resource for identifying eye conditions in the public domain. Comprising a structured ophthalmic database, this dataset features a "real-life" collection of 5,000 patients drawn from various hospitals and medical facilities across China.

The dataset comprises various details, including factors such as age, along with color fundus photographs (fundoscopy) from both the left and right eyes. Additionally, diagnostic keywords supplied by medical professionals are included as part of the dataset. For the specific task of ocular disease categorization, the fundus images within the dataset are classified into four distinct groups: normal, diabetes, cataract, and glaucoma, labeled as N, D, C, and G, respectively. In total, the dataset comprises 5,000 color fundus photographs, strategically divided into training and testing subsets for comprehensive analysis and model evaluation.

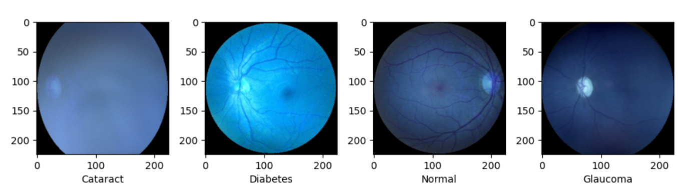

Fig. 1. Sample Images from Dataset

IV. Methodology

A. Experimental Setup

The experiment took place in a Google Colaboratory notebook, utilizing an Nvidia Tesla T4 GPU with 15 GB of

RAM. The system configuration included 12.7 gigabytes of RAM and 78.2 gigabytes of disk space.The choice of a GPU was motivated by the prevalence of matrix multiplication in machine learning and transformers. GPUs excel at parallelizing these computations, resulting in faster processing times. This hardware configuration aimed to expedite the experiment, given the matrix-heavy nature of deep learning tasks.

B. Hyperparameters used

TABLE I
HYPER PARAMETER USED

Hyper Parameter	Value
Epoch	20
Batch Size	32
Loss function	sparse categorical cross entropy loss
Optimizer	Adam
Pooling Layer	Max

Selecting the appropriate hyperparameters is a critical aspect of optimizing model performance, as default settings may not yield the desired results. Our hyperparameter tuning process involved thoughtful considerations for epoch count, batch size, loss function, optimizer selection, and pooling strategy, all aimed at achieving the optimal balance between model complexity and performance for our specific classification task.

Firstly, the concept of epochs was employed, where one epoch represents a complete iteration over the dataset, allowing the model to adjust its weights. In our case, we executed 15 epochs. This number was chosen through careful experimentation, as too few epochs result in underperformance, while an excess of epochs can lead to performance plateauing. Striking the right balance is essential for achieving peak performance.

The batch size, denoting the number of images processed in a single iteration before updating weights through backpropagation, was set at 32. This choice was made after considering the trade-off between count of epochs and batch size required to attain a specific degree of performance. Lower batch sizes necessitate more epochs for convergence, while larger sizes may lead to quicker convergence but at the risk of overshooting the optimal performance.

For the loss function, we opted for sparse categorical cross-entropy. This choice was dictated by the nature of our task involving four classes. While simple cross-entropy is suitable for binary classification, the sparse variant accommodates scenarios with multiple classes, ensuring effective optimization for our specific use case.

The Adam optimizer was selected for its prevalence and effectiveness in the research industry. Known for combining the benefits of both the Adagrad and RMSprop optimizers, Adam adapts learning rates individually for each parameter, providing efficient and reliable convergence.

In the concluding stage, a pooling layer utilized max pooling. Max pooling entails the selection of the maximum value from a set of values, effectively diminishing dimensionality and capturing the most prominent features in the data. This approach aids in retaining critical information while reducing computational complexity, contributing to the model's ability to focus on key aspects and enhance its feature extraction capabilities. This pooling technique was chosen based on its proven efficacy in retaining crucial information while downsampling.

C. Model Comparison

TABLE II
MODEL PERFORMANCE COMPARISON

Model Name	Accuracy (%)	Time elapsed(s)
EffecientNet V2	78.12	161.3
EffecientNet V1	76.21	60.6
MobileNet V2	72.23	164.5
Resnet50V2	66.51	164.7
Inception	65.73	163.6

Upon evaluating the performance of various deep learning models, it's evident that InceptionNet V3 yielded the lowest accuracy among the models tested. ResNet50V2 demonstrated slightly better performance, offering a reliable alternative. However, the standout performers were MobileNetV2 and EfficientNetV2, both exhibiting significantly better accuracy.

EfficientNetV2, in particular, achieved the highest accuracy at 78.12%, outperforming its predecessor, EfficientNetV1, which attained 76.21%. Despite its accuracy, EfficientNetV2 does come with a drawback of higher computational time, taking 161.3 seconds to complete the evaluation. MobileNetV2 also performed well with an accuracy of 72.23%, although it lagged behind EfficientNetV2 in terms of efficiency, taking 164.5 seconds.While ResNet50V2 provides a competitive option, EfficientNetV2 stands out for its high accuracy, albeit with a trade-off in computational time.

D. Dataset Prepocessing

Preprocessing is essential in any machine learning project. We also did neccessry preprocessi. We applied augmentation to increase the diversity of images, and to reduce overfitting. So that it can enhance our model's ability to recognize unseen data. Then we manually encoded the four class labels and splitted the dataset into a train, validation, and test set.

E. Our Model

After preprocessing the dataset, we proceed to train our model using a transfer learning-based architecture, which utilizes the EfficientNet V2 B1 as its baseline. EfficientNet V2 offers a range of variants from B0 to B3, each with different model sizes and complexities. Among these options, we specifically chose B1 due to its optimal balance between performance and model size, ensuring a lightweight design without compromising accuracy. Notably, the largest variant of EfficientNet V2 is significantly larger than B1, yet the marginal improvement in performance does not justify the increased computational demands.

Following the EfficientNet V2 B1, the architecture includes a flatten layer with 62,720 nodes. This layer reshapes the output from the preceding convolutional layers into a one-dimensional array, preparing it for additional processing.

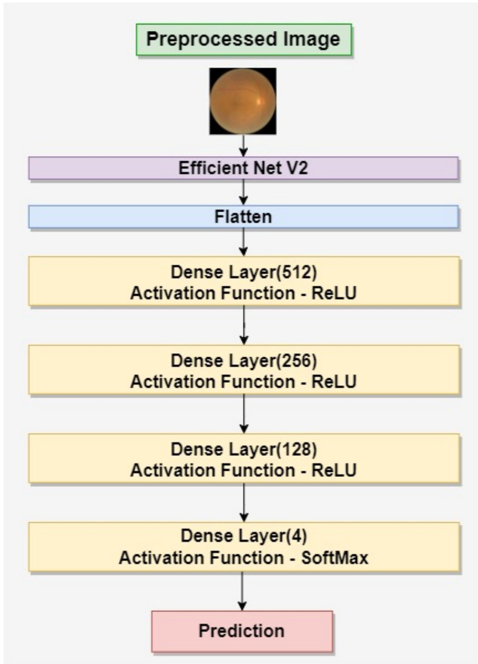

Fig. 2. Model Architecture

Subsequently, a dense layer with 512 outputs is applied, incorporating a Rectified Linear Unit (ReLU) activation function. The integration of the ReLU activation function serves to introduce non-linearity to the model, thereby augmenting its ability to discern intricate patterns within the data. This enhancement contributes to the model's overall effectiveness in capturing nuanced features and improving its learning capabilities.

Continuing the architecture, another dense layer is incorporated with 256 outputs and a ReLU activation function. This intermediate layer further refines the learned features. Subsequently, a third dense layer follows, comprising 128 outputs with a ReLU activation function, contributing to the hierarchical abstraction of features within the model.

The final layer consists of four outputs, representing the number of classes in the classification task. A softmax activation function is applied to this layer, normalizing the output values to obtain probabilities for each class. The softmax function ensures that the class with the highest probability is considered as the predicted output. Given the four classes in the task, the final output layer has four nodes, each corresponding to a distinct class.

F. Federated Learning

Initially, the central server has the global model. Copies of this global model are sent to each local hospital or medical device involved in the process. Each hospital independently trains its local model using its own medical data. After training their local models, each hospital computes the weight updates based on the differences between their local model's performance and the global model's performance. These updates are essentially gradients. Only the updates (gradients) are sent from each hospital's local model to the central federated server. This ensures that sensitive patient data remains secure and private at each hospital. The central federated server applies the aggregated update to the global model, adjusting it to incorporate the collective knowledge from all participating hospitals.

To prevent poisoning the global model for the detection of ocular diseases, measures must be implemented throughout the model's development, training, and deployment phases. Firstly, data integrity is paramount; the dataset used for training should be curated meticulously to ensure it is diverse, representative, and free from biases that could compromise the model's accuracy. Regular audits and updates to the dataset are necessary to incorporate new information and maintain relevance over time.

Furthermore, robust security protocols must be in place to safeguard against adversarial attacks that could manipulate the model's behaviour. Continuous monitoring and validation of the model's performance on real-world data are essential to identify any deviations or potential vulnerabilities. Before accepting contributions from federated nodes, thorough validation of incoming data should be conducted to ensure its integrity and authenticity. Trustworthiness of federated nodes is significant, and only nodes with a proven track record of reliability and accuracy should be allowed to contribute to the global model. Suspicious or potentially malicious data must be filtered out before aggregation to prevent any compromise in the model's performance. Assigning varying weights to different nodes based on their historical performance further enhances the security of the model. Nodes with a demonstrated track record should be assigned higher weights in the

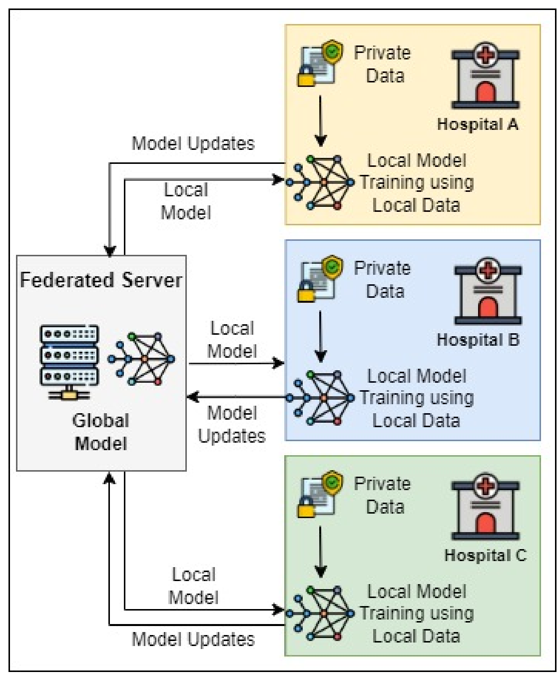

Fig. 3. Federated Learning Workflow

aggregation process, reinforcing the contribution of reliable sources. Continuous monitoring of federated nodes is essential to promptly detect any suspicious activities or attempts at poisoning the model, enabling quick intervention to maintain the integrity and effectiveness of the global ocular disease detection system.

Collaboration with experts in ophthalmology and healthcare professionals is crucial to incorporate domain-specific knowledge and ensure the model aligns with the latest medical advancements. Transparency in the model's decision-making process, ethical considerations, and adherence to privacy regulations are vital to build trust among users and stakeholders. Regular updates and improvements should be implemented based on feedback and advancements in ocular disease detection technology to enhance the model's overall reliability and efficacy.

V. Result and Analysis

A. Summary of our Model

TABLE III
Model Performance Over Epochs

Epoch	Accuracy (%)
1	65.62
2	74.08
3	78.34
4	83.84
5	86.02
6	86.93
7	90.11
8	92.83
9	93.91
10	93.16
11	92.70
12	95.47
13	94.53
14	93.91
15	94.85
16	95.39
17	**95.93**
18	93.40
19	94.67
20	95.88

We can see that the model performance with the increase in epochs.

B. Limitations

1) Resource Limitations:: Transfer and federated learning require substantial computational resources, including powerful hardware and efficient data storage. Many healthcare facilities, especially in less-developed regions, may lack the necessary infrastructure, hindering the implementation of these advanced techniques.

2) Algorithmic Challenges:: Developing effective algorithms for the detection of ocular diseases through transfer and federated learning can be challenging. Ensuring the models generalize well across different datasets and populations while maintaining high accuracy, requires sophisticated algorithms that may not be readily available.

3) Limited Access to Global Knowledge:: In federated learning, models are trained across multiple decentralized datasets. However, access to diverse and comprehensive datasets may be limited, leading to biased models that may not perform well on certain populations. Limited access to a globally representative dataset could undermine the generalizability of the models.

4) Security Risks:: Federated learning involves the exchange of model updates between decentralized devices or servers. This introduces security risks, as the communication between nodes could be vulnerable to attacks. Ensuring the confidentiality and integrity of patient data during the federated learning process is a critical concern.

5) Heterogeneous Data Distribution:: Ocular disease datasets may vary significantly in terms of data distribution, imaging technologies used, and data quality. Handling these variations effectively poses a challenge for transfer and federated learning algorithms, as they need to adapt to the diverse characteristics of different datasets to maintain optimal performance.

6) Privacy Concerns:: Privacy holds considerable importance in healthcare, and the detection of ocular diseases is no different. Federated learning addresses this concern by training models on decentralized data sources without sharing raw data. Nevertheless, safeguarding the privacy of sensitive patient information during the model training process remains a complex challenge that requires thorough consideration.

7) Interoperability Challenges:: Different healthcare systems may use diverse data formats, standards, and protocols. Achieving interoperability between these systems to facilitate the seamless implementation of transfer and federated learning is a considerable challenge that must be addressed for these methods to be widely adopted in ocular disease detection.

8) Ethical Considerations:: The deployment of transfer and federated learning in healthcare raises ethical concerns, including transparency, accountability, and the potential for unintended biases in the models. Addressing these ethical considerations is crucial to gaining public trust and ensuring responsible use of the technology in ocular disease detection.

VI. Conclusion

Federated learning, in conjunction with transfer learning techniques, provides a promising path for the prediction of ocular diseases.By leveraging the collective knowledge from various datasets while respecting data privacy, these methods demonstrate enhanced model performance. Transfer Learning optimizes model training by utilizing pre-existing knowledge, while Federated Learning facilitates collaborative learning across distributed datasets without compromising sensitive patient information. In this research, the investigation highlights the effectiveness of deep learning models, notably EfficientNetV2 and MobileNetV2, in achieving superior accuracy when categorizing ocular diseases. Later extended federated learning facilitates collaborative learning across distributed datasets without compromising sensitive patient information, which not only improves diagnostic accuracy but also establishes a framework for scalable, privacy-preserving healthcare solutions. Further advancements and refinements in these methodologies hold the potential to revolutionize ocular disease diagnosis and treatment in clinical settings. Future work in this research aims to focus on enabling real-time detection capabilities while advancing the development of more efficient and secure healthcare solutions.

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