IARJSET

ISSN (O) 2393-8021, ISSN (P) 2394-1588

International Advanced Research Journal in Science, Engineering and Technology

Impact Factor 8.066 ⁜ Peer-reviewed & Refereed journal ⁜ Vol. 12, Issue 5, May 2025

DOI: 10.17148/IARJSET.2025.125182

Deep Learning Approach to Detect Pediatric Glaucoma

Chaitrashree R [1], S Karthik [2], Sachin B [3], Sandhya M [4], Sujeeth M [5]

Assistant Professor, Department of ISE, MITM, Mysore, VTU Belagavi, India[1]

UG Students, Department of ISE, MITM, Mysore, VTU Belagavi, India[2-5]

Abstract: This project develops a deep learning system for classifying medical images using the MobileNetV2 architecture and transfer learning. The images are preprocessed with resizing and normalization, and the model is trained for 25 epochs with custom layers to improve accuracy and F1 score. It also includes a Gradio interface for real-time predictions, enhancing diagnostic efficiency. The tool is designed to support medical professionals in areas with limited resources by offering a reliable and accessible diagnostic solution.

Index Terms—Deep Learning, Medical Image Classification, MobileNetV2, Transfer Learning, Image Preprocessing, Gra-dio Interface, Real-Time Predictions, Resource-Limited Settings, Glaucoma Detection, F1-Score, Diagnostic tool.

Keywords: Detecting Pediatric Glaucoma

I. INTRODUCTION

Medical image classification has emerged as a vital domain within healthcare, providing automated solutions that assist in the early diagnosis and treatment planning for a variety of dis- eases. Deep learning models, particularly convolutional neural networks, have shown great potential in analyzing complex image patterns and effectively identifying irregularities. This project centers on the implementation of the MobileNetV2 architecture, a pre-trained model recognized for its lightweight structure and efficiency, to effectively classify medical images. To enhance performance, transfer learning is employed, allowing the model to adjust its pre-trained weights for the specific task. Images are preprocessed through resizing and normalization to maintain uniformity and boost computational efficiency. The system features a Gradio interface for real-time image uploads and predictions, ensuring it is user-friendly and accessible for medical professionals. By integrating accuracy, scalability, and usability, this project strives to deliver a practical tool that supports diagnostic workflows, especially
in resource-limited environments.

II. LITERATURE SURVEY

Early fire detection in farms is an important research area, helped by machine learning and deep learning. These technologies make it possible to create systems that spot fire patterns in images, which can help reduce crop damage. The studies listed below form the basis for this project:

Reddy et al. [1] developed a fire detection and monitoring system using IoT and machine learning. Their work integrated environmental sensors with machine learning algorithms for real-time fire detection. While their focus was on urban environments, their approach highlights the potential for combining sensor data, such as temperature and humidity, with machine learning for agricultural applications.

Jayathilaka et al. [2] proposed a smart forest fire detection system using Convolutional Neural Networks (CNNs). Their research demonstrated CNNs' effectiveness in identifying fire patterns from images, which is directly relevant to this project's focus on CNN-based fire detection for agricultural fields.

Chen et al. [3] explored real-time fire detection in agricultural fields using computer vision and deep learning. By em-ploying CNNs on camera-captured images, they showcased the feasibility of early fire detection, aligning with the objectives of this project to monitor crops efficiently.

Maheswari et al. [4] introduced a hybrid farm fire detection system integrating IoT sensors with neural networks. Their work addressed challenges like poor visibility and limited data by combining environmental and image data. While this project focuses on optimizing CNNs for image-based detection, their hybrid approach provides valuable insights.

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Lee et al. [5] utilized YOLOv4 and remote sensing for forest fire detection, demonstrating real-time detection in dynamic visibility conditions.
Though applied to forests, their method- ology can be adapted to agricultural fields, offering timely responses to fire outbreaks.

Zhang et al. [6] combined convolutional neural networks (CNNs) with Long Short-Term Memory (LSTM) networks to study fire behavior in video streams. Their temporal modeling approach is a potential extension for continuous fire monitor- ing in agricultural settings using farm cameras.

Kumar et al. [7] focused on drone-based fire detection, leveraging aerial imagery for large-scale surveillance. Al- though this project does not include drones, their method highlights future opportunities for expanding coverage in agri- cultural fire monitoring.

Singh et al. [8] investigated edge computing for fire de- tection, optimizing models for real-time processing on edge devices. This approach could enhance the scalability and responsiveness of fire detection systems in agricultural fields by enabling mobile and IoT-based alerts.

III. BLOCK DIAGRAM AND SYSTEM ARCHITECTURE

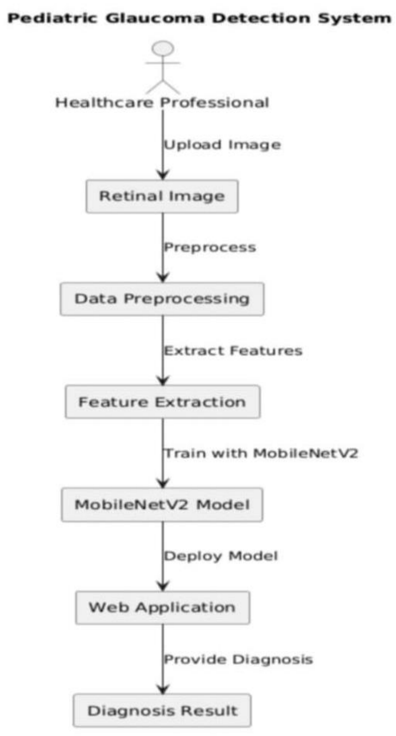

Fig. 1. Block Diagram

1. User Interaction: Healthcare Professional Uploads Image
The system begins with a healthcare professional, such as an ophthalmologist or technician, uploading a retinal image of a pediatric patient. This step is critical, as the accuracy of the diagnosis relies heavily on the quality and clarity of the retinal image provided. The image is usually captured using specialized medical equipment like a fundus camera, which captures high-resolution images of the retina, optic nerve, and surrounding blood vessels.

2. Retinal Image Acquisition
Once uploaded, the retinal image serves as the core input for the detection system. This image contains crucial visual data, such as the optic disc, optic cup, and retinal nerve fiber layer, all of which play a significant role in diagnosing glaucoma. Pediatric glaucoma is especially challenging to detect due to the subtle symptoms and variations in eye anatomy compared to adults, which makes retinal imaging even more important.

3. Data Preprocessing

In this stage, the uploaded image undergoes preprocessing to improve its quality and make it suitable for analysis. Preprocessing techniques may include resizing the image to a fixed dimension, removing background noise, enhancing contrast, and normalizing pixel values. These operations help standardize the input for the machine learning model, ensuring consistency and accuracy across various samples. Data augmentation might also be applied during training to increase dataset diversity and prevent overfitting.

4. Feature Extraction

After preprocessing, the system extracts key features from the image. These features are essential patterns or structures within the retinal image that are indicative of glaucoma. For pediatric glaucoma detection, features such as the cup-to-disc ratio, optic disc boundaries, and retinal vessel structure are particularly important. This step transforms the raw image data into a format that the deep learning model can analyze effectively.

5. MobileNetV2 Model Training

The extracted features are then passed into a deep learning model known as **MobileNetV2**. This model is a lightweight convolutional neural network optimized for fast performance on mobile and embedded devices, making it suitable for real-time diagnosis. The model is trained using a labeled dataset of retinal images, where each image is classified as glaucomatous or non-glaucomatous. Through training, the model learns to differentiate between healthy and affected retinal patterns.

6. Web Application Deployment

Once the MobileNetV2 model has been trained and validated, it is deployed into a **web application**. This allows healthcare providers to use the system through a user-friendly interface. The web application accepts new retinal images, runs them through the trained model, and displays diagnostic results. This setup provides remote accessibility and facilitates large-scale screening, even in rural or under-resourced areas.

7. Diagnosis Result

The final stage of the system provides the **diagnostic output**. The web application displays whether the input image shows signs of pediatric glaucoma. The result may also include a confidence score indicating the model's certainty in its prediction. This outcome aids healthcare professionals in making timely decisions for further medical examination or treatment, thereby enhancing the chances of early detection and prevention of vision loss in children.

IV. METHODOLOGY

1. Dataset Acquisition

• Source: The Eagle dataset was selected for this study, comprising retinal images annotated for glaucoma di- agnosis. This dataset includes images categorized into different classes (e.g., healthy, glaucoma).
• Size and Composition: The dataset includes a specific number of images, which are divided into different categories. Each category represents a class, and the images are distributed among these classes based on their type.
• Ethical Considerations: Discuss any ethical considerations regarding the use of medical data, including consent and privacy.

2. Data Preprocessing

• Image resizing: All images were adjusted to a size of 224x224 pixels to match the input needs of the MobileNetV2 model.
• Normalization: The pixel values were adjusted to be between 0 and 1 by dividing them by 255. This makes it easier and faster for the model to learn during training.
• Data Augmentation: To make the training set more di- verse and help the model perform better, techniques like rotating, flipping, and adjusting brightness were used.

3. Model Architecture

• MobileNetV2 Overview: Explain the architecture of Mo- bileNetV2, emphasizing its lightweight design and efficiency in processing.
• Layer Structure: Detail the key components of the model, including convolutional layers, depth-wise separable convolutions, and activation functions (ReLU, Softmax).
• Transfer Learning: Discuss the approach of using pre- trained weights from ImageNet and the benefits of trans- fer learning in reducing training time and improving accuracy.

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4. Model Training

• Environment Setup: Describe the use of Google Colab for training, including GPU specifications and any libraries (TensorFlow, Keras) used.
• Training Procedure: The training process involves feeding the model data in small groups, called batches. It runs for a set number of cycles, known as epochs, to improve accuracy. Optimization methods like Adam or SGD help adjust the model's learning to make better predictions.
• Loss Function: The model uses a loss function, such as categorical cross-entropy, to measure how well it makes predictions. In multi-class classification, this function helps compare the predicted probabilities with the actual class, guiding the model to improve accuracy during training.
• Validation Strategy: The validation set was used to check how well the model was performing. It helped track accuracy and detect overfitting. Techniques like early stopping were used to stop training when the model started to lose generalization, ensuring better real-world performance.

5. Model Evaluation

• Performance Metrics: Accuracy, precision, recall, and F1- score help evaluate how well the model performs.
• They measure correctness, the ability to find positive cases, and balance between precision and recall.
• Test Set Evaluation: The model was tested on a separate set of data that it hadn't seen before to check how well it can handle new, unseen examples. This helps evaluate how well the model generalizes to real-world situations.

6. Validation and Testing

• User Testing: Discuss any user testing conducted to gather feedback on the application's usability and effectiveness., Iterative Improvements: Highlight any changes made to the model or application based on feedback from initial users.

V. RESULT AND PERFORMANCE ANALYSIS

The code uses MobileNetV2 to classify medical images effectively. After training for 25 epochs, it achieves good accuracy and measures performance using precision and F1- score to ensure balanced predictions. The model works well on unseen test data, showing its ability to generalize. It also includes a user-friendly Gradio interface for real-time image classification. Overall, it provides a simple and efficient tool for diagnosing medical conditions from images.

Fig 3. No indications of Pediatric Glaucoma detected

Fig 4. Signs of Pediatric Glaucoma detected

VI. FUTURE SCOPE

• Extend the system to diagnose other retinal diseases, such as diabetic retinopathy and macular degeneration, using the same framework.

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- Make the model work efficiently on devices like smart- phones or portable kits so it can diagnose problems offline, even in remote areas.
- Incorporate feedback from healthcare professionals to refine accuracy, usability, and clinical acceptance.
- Create scalable cloud-based solutions for centralized storage and large-scale implementation in hospitals.
- Expand the dataset with diverse retinal images from various demographics to improve generalization and reduce biases.

VII. CONCLUSION

This mission successfully implements a lightweight and efficient clinical image type gadget the use of the MobileNetV2 architecture, demonstrating excessive accuracy and real-time diagnostic capabilities via preprocessing, switch getting to know, and a user-pleasant Gradio interface, the model presents handy and scalable answers for healthcare experts. The gadget is in particular proper for aid-confined settings, supporting early disorder detection and improving clinical effects. universal, it bridges the distance between superior device mastering models and practical, real-world scientific programs.

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