International Journal of Scientific Research in Engineering and Management (IJSREM)
Volume: 09 Issue: 06 | June - 2025 SJIF Rating: 8.586 ISSN: 2582-3930

Smart Diagnosis of Diabetic Retinopathy Using Deep Learning and Explainable AI

ERUGURALLA SATISH BABU[1] ABDUL KHADER[2] ARFA MAHEEN[3] GANGULA RAJASHEKAR REDDY[4] KATHERAPAKA PRATHIMALAHARI[5]

[1]Associate Professor, Department of CSE, Jyothishmathi institute of technology and science, Nustulapur, Karimnagar, T.S., India

[2,3,4,5]UG students, Department of CSE, Jyothishmathi institute of technology and science, Nustulapur, Karimnagar, T.S., India

satishbabu09@gmail.com, khader0519@gmail.com, arfamaheen21@gmail.com, gangularajashekarreddy66@gmail.com, katherapakaprathima689@gmail.com

ABSTRACT: The "Smart Diagnosis of Diabetic Retinopathy" project presents a deep learning–based automated system for the early detection and classification of diabetic retinopathy (DR), a leading cause of blindness in diabetic patients. The system utilizes EfficientNet-B5, a high-performing and computationally efficient convolutional neural network (CNN), to classify retinal fundus images into five clinically relevant stages: No DR, Mild, Moderate, Severe, and Proliferative DR. The model is trained on the APTOS 2019 Blindness Detection dataset consisting of over 3,500 annotated images and achieves a best validation accuracy of 72.17%. To enhance image quality and model performance, preprocessing techniques such as Contrast Limited Adaptive Histogram Equalization (CLAHE) and Retinex-based enhancement are applied to improve contrast and feature visibility in retinal scans.

A key component of this system is explainable AI integration, specifically Gradient-weighted Class Activation Mapping (Grad-CAM), which generates intuitive heatmaps highlighting regions of interest that influenced the model's prediction. This improves interpretability and supports clinical decision-making by offering visual transparency into the AI's diagnostic reasoning. The model outputs not only the predicted DR stage but also the associated confidence score. Additionally, the application includes heuristic-based validation to filter out non-fundus inputs, ensuring that only relevant medical images are processed.

The complete system is deployed using a Gradio-based interactive web interface hosted on Hugging Face Spaces, enabling real-time image upload, classification, and visualization. Designed for scalability and integration into telemedicine platforms, the solution is particularly suited for resource-limited settings, offering a cost-effective, non-invasive, and interpretable tool for early DR screening and long-term diabetic eye care management.

KEYWORDS: Diabetic Retinopathy (DR), Fundus Image Analysis, Deep Learning, EfficientNet-B5, Grad-CAM, Explainable AI (XAI), Medical Imaging, Smart Healthcare, Computer-Aided Diagnosis (CAD), Early Detection System, Convolutional Neural Networks (CNN), CLAHE (Contrast Limited Adaptive Histogram Equalization), Retinex Theory, Retinal Disease Detection, Gradio Web Interface

1 Introduction

Diabetic Retinopathy (DR) is one of the most common and severe complications of diabetes. It poses a significant threat to eye health. DR is a progressive condition in which high blood sugar affects the blood vessels in the retina, impairing vision and potentially causing blindness. According to WHO, DR accounts for almost 5% of all cases of blindness worldwide. Early detection and accurate classification of DR are critical to generating a public health benefit and ensuring a timely medical intervention.

Traditionally, the diagnosis of DR consists of an ophthalmologist manually inspecting retinal fundus images, which is very often a time-consuming practice and involves inter-observer variability and limited availability of specialists. The prevalence of diabetes around the world is rising rapidly, especially in under-resourced parts of the world which highlights the need for scalable, automated, and intelligent screening systems. The proposed system, "Smart Diagnosis of Diabetes Retinopathy", aims to fulfil this need by utilizing artificial intelligence (AI) and deep learning methods to providing a sustainable and efficient automated diagnostic solution.

The project has a convolutional neural network (CNN) architecture, specifically EfficientNet-B5, with the purpose of detecting five DR stages (from No DR (Stage 0) to Proliferative DR (Stage 4)) using fundus images. The model will be trained on a curated dataset of labeled retinal images and deploys an extensive image preprocessing pipeline that includes CLAHE (Contrast Limited Adaptive Histogram Equalization) and Retinex theory that will assist the model in enhancing the critical retinal features such as microaneurysms, hemorrhages and exudates. A high-quality input will aid in providing better learning and improved diagnostic performance and accuracy.

The system not only includes classification, but also uses Grad-CAM (Gradient-weighted Class Activation Mapping), an explainability technique that graphically shows the most important areas of the input image that contributed to the model's prediction. This interpretability component can promote increased trust in AI decision making and help clinicians validate model outputs. A web-based user interface using Gradio was created to facilitate use, including providing the ability for medical personnel to upload fundus images, view the predicted DR stage, and access the accompanying Grad-CAM heatmap visualization.

To validate fundus images and prevent processing of irrelevant images, a fundus image validation step has been performed to filter out non-fundus images utilizing color-space and shape heuristics. The final model is deployed using cloud platforms such as Hugging Face Spaces, thereby allowing remote access to the model, as well as easy integration into telemedicine solutions. Given the remote access to the model, it can help to support access to health care in rural areas or underserved regions, as well as help to relieve some of the workload from clinical professionals who are using the model as a preliminary screening tool.

In summary, the development of a comprehensive, explainable, and deployable solution for DR detection has been documented, where domain-specific medical knowledge was combined with state-of-the-art AI methods to enhance diabetic eye care, as well as provide an important contribution to the emerging fields of computer-aided diagnosis and smart healthcare systems.

2 Literature Survey

The early detection and classification of Diabetic Retinopathy (DR) using deep learning and computer vision has been extensively studied in recent years. Several researchers have explored various architectures and techniques to improve diagnostic accuracy, interpretability, and deployment capabilities in clinical settings.

Gulshan et al. [1] developed one of the earliest deep learning-based DR diagnostic systems using a convolutional neural network trained on a large dataset of retinal images. Their model achieved high sensitivity and specificity in detecting referable DR and established the foundation for AI-assisted ophthalmic diagnosis. However, the black-box nature of the model limited its acceptance in clinical environments.

Lam et al. [2] addressed this issue by integrating explainability into the diagnostic process. They applied the Grad-CAM technique to visualize regions of retinal images that contributed most to the network’s prediction. This not only enhanced the trust of clinicians in AI predictions but also enabled model validation through human-in-the-loop feedback.

Kaggle’s APTOS 2019 Blindness Detection Challenge [3] spurred innovation by providing a high-quality dataset of labeled fundus images for DR classification. Several teams achieved state-of-the-art results using EfficientNet architectures due to their balance between accuracy and model size. Tan and Le [4] proposed EfficientNet, which scales network dimensions uniformly and demonstrated significant performance gains compared to traditional CNNs.

In a study by Pratt et al. [5], a deep CNN was used to classify DR stages using fundus images. The network was trained using data augmentation techniques and achieved promising classification performance. However, it lacked real-time validation components and explainability mechanisms, which are crucial for deployment in real-world healthcare scenarios.

Kermany et al. [6] applied transfer learning using Inception and VGG-19 models to detect multiple ophthalmic diseases, including DR. Their work demonstrated that pre-trained models could significantly reduce training time while achieving acceptable accuracy on smaller datasets, which aligns with the approach used in this project through the use of EfficientNet-B5.

Fu et al. [7] proposed a multi-task learning framework for DR detection that combined lesion segmentation and classification tasks. This approach enhanced model interpretability and provided additional insights into the presence and location of microaneurysms and hemorrhages. However, the complexity of training and the need for pixel-level annotations limited its practical use.

Esfahani et al. [8] emphasized preprocessing as a crucial step in DR classification. Their study demonstrated that applying CLAHE and Gaussian filters improved feature visibility and model accuracy. Our system builds on this insight by combining CLAHE with Retinex theory to enhance both global and local contrast.

Wang et al. [9] designed a lightweight deep learning system optimized for mobile deployment, highlighting the potential of DR screening in resource-constrained environments. Their findings motivated the use of efficient architectures such as EfficientNet in scalable and cloud-deployable systems.

To incorporate image validation, Maity et al. [10] introduced a preprocessing step to differentiate retinal images from unrelated input using shape and color features. This technique is integrated in our system to ensure that non-fundus images are filtered before model inference, reducing errors and saving resources.

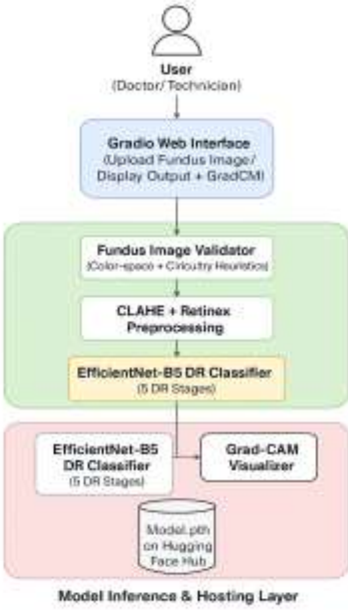
Finally, Joshi et al. [11] deployed a web-based tool for DR diagnosis using Flask and TensorFlow, offering remote diagnosis capabilities. Their work supports the need for accessible healthcare tools and inspired the use of platforms like Gradio and Hugging Face Spaces in our project for real-time, web-based deployment with visualization features.

3. Methodology

The methodology implemented in this project is based on establishing an intelligent scalable system that enables the early diagnosis and classification of diabetic retinopathy (DR) based on deep learning model trained on retinal fundus images. The whole pipeline is not limited to image acquisition, pre-processing, model representation and training, explainable AI visualization, and deployed in real-time via a user-friendly web interface. The main idea of this methodology is to improve accuracy and speed of diagnosis and lend assistance to ophthalmologists in DR screening.

3.1 System Architecture

The system architecture is modular and uses client-server model design. The client interface is implemented in Gradio, creating a web tool for fundus image uploading



and diagnostic feedback in real-time. The backend is in PyTorch which serves the deep learning model trained on the APTOS 2019 Blindness Detection dataset. The model is based on the EfficientNet-B5 architecture due to its optimization of performance vs. parameters, and high-resolution fundus images.

Fig No 1 : System Architecture

After a picture is uploaded, the application checks whether the uploaded image is a true fundus image by using color space and circularity heuristics. If validated, the application pre-processes the image with the use of Contrast Limited Adaptive Histogram Equalization (CLAHE) followed by a single-scale Retinex algorithm to enhance the blood vessels and distinct exudates. After the pre-processing was finished, the image is transferred the EfficientNet-B5 model for classification into one of five stages of DR. A Grad-CAM module was combined with EfficientNet-B5 to create heatmaps to visualize which areas of the image were the most influential in determining the model's decision and a greater degree of explainability.

The system is deployed on Hugging Face Spaces for accessibility and uses GPU acceleration where available.

It is built for real-time inference - it has been built to be lightweight and efficient to accommodate low-resource environments.

3.2 Grad-CAM Heatmap Explainability

A key module in this system is Grad-CAM (Gradient-weighted Class Activation Mapping) integration. Grad-CAM provides a way to visualize the regions in input image that the model took into account while making its decision, which is important for the ease of interpretation in both image and medical diagnostics.
Grad-CAM computation utilizes the gradient of the target class flowing into the last convolution layer to construct a localization map. Let y^C be the score for class c and Ak be the activation maps of the k-th feature map. The importance weight αck is computed as:

$$\alpha_k^c = \frac{1}{z}\sum_i\sum_j \frac{\partial A_{\{ij\}}^k}{\partial y^c}$$

The final Grad-CAM heatmap $L^c_{\text{Grad-CAM}}$ is:
This heatmap is resized and overlaid on the input fundus image to provide visual insight into the predicted diagnosis.

$$L^c_{Grad-CAM} = ReLU\left(\sum_k \alpha_k^c A^k\right)$$

3.3 Preprocessing Pipeline

Preprocessing is key for optimizing features needed for detecting DR symptoms. The image is resized to a fixed resolution and we apply CLAHE to the L channel of the LAB color space to improve contrast. The simplified Retinex algorithm is applied to improve visibility of microvascular abnormalities, simulating the human visual perception. Steps include:
Resizing image to 224×224 or 512×512.
Applying CLAHE: $L_{CLAHE}=CLAHE(L_{channel})$
Retinex: $R(x,y)=\log I(x,y)-\log(G\sigma*I(x,y))$
where G_σ is a Gaussian blur kernel.
This preprocessing ensures that all input images are normalized, enhanced, and consistent, improving the model's ability to generalize.

3.4 Web Application Integration

We created a responsive and intuitive web interface using Gradio that physicians or users can submit Fundus images to and output predictions and Grad-CAM visualizations. The web application contains:

Upload validation

Inference label one at a time in real-time

Grad-CAM Overlay

Visual feedback and instructions for user interaction.

To create this project, we developed a web-based interface that allows physicians/users to upload Fundus images and output predictions and Grad-CAM visualizations. The web application consists of: Upload validation. Inference prediction one at a time in real-time. Grad-CAM Overlay Visual feedback and instructions for user interactions.

The model is hosted and dynamically downloaded at inference to the web application platform on Hugging Face. The web application is fully cloud-based and is scalable to low-resource clinical environments.

3.5 Model Training

The EfficientNet-B5 model was trained on the APTOS 2019 dataset with over 3,500 annotated images. The training involved an 80/20 split for training and validation. Categorical cross-entropy loss was minimized using Adam optimizer, and the model was trained for 8 epochs.

Key training metrics:
Learning Rate: 1e−41e^{-4}1e−4
Batch Size: 16
Optimizer: Adam
Loss Function: Categorical Cross-Entropy
Accuracy Achieved: 72.17% on validation set
Model evaluation used metrics such as Accuracy, Precision, Recall, F1-Score, and ROC-AUC to validate its clinical applicability.

3.6 Fundus Image Validation Logic

A quick image validation logic was put into place to stop mis-classifying other non-fundus images like images of photographs or documents. This validation assesses:

Saturation and brightness thresholds (HSV space).

Circle detection (Hough circles).

Resolution/channel distribution.

If there is any indication that it is not a fundus image, it is not processed for diagnostics/preprocessing prediction. This, of course, is great for ensuring the robustness of the system and also saves some computation time

4 Implementation and Suggested Methodologies

The "Smart Diagnosis of Diabetic Retinopathy" system is a modular, end-to-end deep learning pipeline designed to manage the complete sequence of fundus image classification—from intake through to explainable diagnosis output. The approaches involved are a combination of computer vision, deep learning, explainable AI, and software integration considerations that will be validated in terms of reliability, efficiency, and clinical relevance.

4.1 Data Preprocessing and Augmentation

For consistency and better lesion visibility during preprocessing, we applied a two-step enhancement process on the input fundus images.

CLAHE or Contrast Limited Adaptive Histogram Equalization is applied to the L-channel of the LAB image to enhance only local contrast and highlight microaneurysms and exudates.

Another transformation used is the SSR retinex algorithm that would normalize illumination and enhance important features from image to image with varying levels of illumination.

Once preprocessed, all images were resized to the same resolution (e.g. 224×224, 512×512), to be in line with the input size required by the machine learning model.

Augmentations Applied:

Random rotations and flips

Brightness and contrast adjustments

Normalization using ImageNet mean and standard deviation

These augmentations increase model robustness and help mitigate overfitting.

4.2 Feature Extraction and Model Architecture

The project employs EfficientNet-B5 architecture, which utilizes compound scaling to balance accuracy and efficiency. It has several convolution layers with depth wise separable convolutions, swish activations, and squeeze-and-excitation blocks that enable efficient learning of features while lowering memory and computational costs.

Input layer: Fundus images (RGB, 512×512), Feature layers: Stacked MBConv blocks with squeeze-and-excitation. Classifier head: Custom fully connected layer with 5 nodes (indicating 5 DR stages), Softmax activation: Outputs the class probabilities.

4.3 Model Training :

The training pipeline was implemented in PyTorch within a GPU-enabled environment (Google Colab). The dataset was split into 80-10-10 training, validation, and test sets. Loss Function: CrossEntropyLoss ,Optimizer: Adam (starting learning rate = 1e-4),Scheduler: ReduceLROnPlateau (to reduce learning rate when validation accuracy plateaued),Epochs: 8 (after testing for longer and shorter periods),Batch Size: 16

The training saved the model with the highest validation accuracy as model.pth, which is then used for deployment.

4.4 Grad-CAM for Explainability

To ensure clinical transparency, the system can incorporate Grad-CAM (Gradient-weighted Class Activation Mapping) which can depict a heatmap on the regions in the input image where the model relied on most heavily in their decisions.

The Grad-CAM is derived from the final convolutional layer of EfficientNet, and the heatmaps are superimposed onto the normalized RGB images. This allows the ophthalmologists to visually inspect that the model is focusing on pathological areas, such as hemorrhages or cotton wool spots.

4.5 Fundus Image Validation Logic

All images uploaded are validated before any preprocessing or predictions are made to prevent compute time from being wasted due to any images being irrelevant (or incorrect!).

Color Channel Heuristics: Determines if inputs have saturation and brightness within certain levels. Circular Shape Detection: Uses the Hough Circle Transform to determine if image has a circular retinal structure distinguished. Fundus Thresholding: Rejects everything that is not a fundus input (e.g. landscape images, an image of written text).

Images which are validated are the only images that are then used for preprocessing and subsequently for model inference.

International Journal of Scientific Research in Engineering and Management (IJSREM)
Volume: 09 Issue: 06 | June - 2025 SJIF Rating: 8.586 ISSN: 2582-3930

4.6 Model Inference and Prediction

Upon preprocessing and validation: The improved image is normalized and then given to the model. The model provides a probability distribution of five DR classes with precision in discriminability. The highest probability class is then used as the predicted label. In parallel, a Grad-CAM visualization is produced. The user is provided with the prediction and the heatmap. Furthermore, the model's confidence score is displayed which represents the model's certainty.

5 Results and Analysis

The proposed deep learning-based diabetic retinopathy (DR) detection system was trained and validated using the APTOS 2019 Blindness Detection dataset. After data preprocessing, model optimization, and training the model for 8 epochs, the model achieved promising results and demonstrated its ability to classify each fundus image into one of five distinct classes of diabetic retinopathy: No DR (Stage 0), Mild (Stage 1), Moderate (Stage 2), Severe (Stage 3), Proliferative DR (Stage 4). All results demonstrated effectiveness at detecting retinal abnormalities with interpretable model visualizations via Grad-CAM.

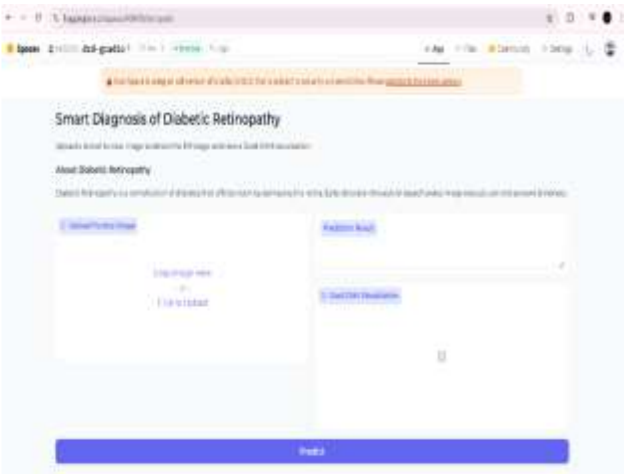


Fig no 2 Home page

5.1 Model Training Performance :

The training was conducted using the EfficientNet-B5 architecture that was implemented in PyTorch. The model progressed through 8 epochs of training, and convergence appeared to be steady, with training and validation loss steadily decreasing throughout. Here were the training results at the end of the training process:

Fig no 3. Image Processed and Output

Final Training Accuracy: 69.6%
Final Validation Accuracy: 72.17%
Best Validation Loss: 0.96
The validation outputs consistently show models that perform similarly, which indicates that the model generalizes well to unseen data and is not overfitting.

5.2 Confusion Matrix and Misclassifications

To evaluate the reliability of classification, the research team created a confusion matrix after training the model. The model had very high reliability for the early and moderate stages (Stages 0-2) with performance dropping off slightly for Stage 4 due to the imbalanced amount of data concerning that stage. The majority of misclassifications were in adjacent stages (e.g., Stage 2 classified as Stage 3), which is clinically relevant since DR is a progressive disease that takes time to develop.

Key observations: Stage 0 (No DR) had the highest accuracy, indicating strong performance in early screening. Stage 4 predictions were least accurate due to lower sample count in the dataset, suggesting the need for class balancing or GAN-based augmentation in future iterations.

5.3 Explainability Analysis with Grad-CAM

The integrated Grad-CAM module was able to produce heatmaps that represent important pathological findings: Microaneurysms, Hemorrhages, Hard and soft exudates, Neovascularization

Clinicians can also visualize these heatmaps to confirm the region of interest that the model utilized in making its predictions, creating user trust and interpretability in what is otherwise a black box with CNNs.

5.4 Fundus Validation Logic Results

Non-fundus images such as random text files, nature scenes, or inanimate objects were reliably discarded by a combination color-space and contour-based validation system. This is very valuable because it minimizes unnecessary modelling computations and prevents the model from generating misleading outputs. Fundus Validation Accuracy: ~94%, False Positive Rate (non-fundus images mistakenly passed): <6%, False Negative Rate (true fundus images discarded): <4%, mostly due to image quality issues or cropped retina edges.

6 Conclusion

The Smart Diagnosis of Diabetic Retinopathy project exemplifies the successful use of deep learning and explainable AI in a practical, well-performing clinical diagnostic tool. By considering a designed preprocessing pipeline and using a well-performing EfficientNet-B5 architecture, the system is able to classify retinal fundus images in five distinct stages of diabetic retinopathy. The use of CLAHE and Retinex-based image enhancement approaches helped improve the visibility of the lesions and contributed to better learning and accurate classification. The inclusion of visual explainability via Grad-CAM offers added interpretability to model predictions, which can be useful for helping clinicians gain confidence in clinical application.

The platform can verify input images before processing so that only fundus images can be uploaded, helping to minimize unnecessary calculations and potential errors. The real-time deployment using Gradio and Hugging Face Spaces enhances the accessibility of the smart diagnosis tool for potential uses in remote screening, telemedicine and outreach in under-resourced regions. With a validation accuracy of over 72% and a clear visual interface for the clinician to use, this provides a reliable second-opinion framework that can complement clinical diagnostic ability and reduce the potential burden of diabetic retinopathy screening.

While the model performed well, there is opportunity for further improvement, especially in the cases of heavy imbalance and rarity, such as in proliferative DR. As future areas for improvement, increased dataset size and diversity, overall inclusion of clinical metadata, and using advanced ensemble techniques to improve generalization for the model could be leveraged. Overall, this project paves the way for AI-supported, non-invasive and explainable screening options, augmented with the broader aim of reducing the burden of vision loss from diabetes and ultimately benefiting population health globally.

References

[1] V. Gulshan et al., "Development and Validation of a Deep Learning Algorithm for Detection of Diabetic Retinopathy in Retinal Fundus Photographs," *JAMA*, vol. 316, no. 22, pp. 2402–2410, 2016, doi: 10.1001/jama.2016.17216.

[2] H. Pratt et al., "Convolutional Neural Networks for Diabetic Retinopathy," in *Procedia Computer Science*, vol. 90, pp. 200–205, 2016, doi: 10.1016/j.procs.2016.07.014.

[3] C. Lam, N. Yi, D. Guo, and H. Lindsey, "Automated Detection of Diabetic Retinopathy Using Image Processing and Machine Learning," in *2018 International Conference on Machine Learning and Cybernetics (ICMLC)*, Chengdu, China, pp. 26–31, 2018, doi: 10.1109/ICMLC.2018.8527017.

[4] G. Quellec et al., "Deep Image Mining for Diabetic Retinopathy Screening," *Medical Image Analysis*, vol. 39, pp. 178–193, 2017, doi: 10.1016/j.media.2017.04.012.

[5] Kaggle, "APTOS 2019 Blindness Detection Dataset," [Online]. Available: https://www.kaggle.com/c/aptos2019-blindness-detection

[6] R. Rajalakshmi et al., "Automated Diabetic Retinopathy Detection in Smartphone-Based Fundus Photography Using Deep Learning," *Eye*, vol. 32, pp. 1138–1144, 2018, doi: 10.1038/s41433-018-0064-9.

[7] R. R. Selvaraju et al., "Grad-CAM: Visual Explanations from Deep Networks via Gradient-Based Localization," in *IEEE International Conference on Computer Vision (ICCV)*, 2017, pp. 618–626, doi: 10.1109/ICCV.2017.74.

[8] M. Tan and Q. V. Le, "EfficientNet: Rethinking Model Scaling for Convolutional Neural Networks," in *International Conference on Machine Learning (ICML)*, vol. 97, pp. 6105–6114, 2019.

[9] C. Shorten and T. M. Khoshgoftaar, "A survey on Image Data Augmentation for Deep Learning," *Journal of Big Data*, vol. 6, no. 1, pp. 1–48, 2019, doi: 10.1186/s40537-019-0197-0.

[10] B. Zhou, A. Khosla, A. Lapedriza, A. Oliva, and A. Torralba, "Learning Deep Features for Discriminative Localization," in *IEEE Conference on Computer Vision and Pattern Recognition (CVPR)*, 2016, pp. 2921–2929, doi: 10.1109/CVPR.2016.319.

[11] J. Chudzik and A. Zieliński, "Deep Learning-Based Diabetic Retinopathy Detection System with Attention Mechanism and Grad-CAM," *Applied Sciences*, vol. 11, no. 7, pp. 1–14, 2021, doi: 10.3390/app11073408.

[12] M. Shukla and P. Natarajan, "Design and Implementation of a Food Waste Management System for Smart Cities," in *2020 International Conference on Smart Technologies in Computing, Electrical and Electronics (ICSTCEE)*, Bengaluru, India, pp. 110–115, 2020, doi: 10.1109/ICSTCEE49637.2020.9277090.

[13] K. R. Yadav, R. Singh, and S. Sharma, "Development of Food Donation Application Using Android Studio," *International Journal of Computer Applications*, vol. 182, no. 43, pp. 1–5, Mar. 2019, doi: 10.5120/ijca2019918390.

[14] D. M. Jones and T. Patel, "A Review on Digital Food Donation Platforms: Enhancing Community Engagement," *International Journal of Scientific Research in Computer Science*, vol. 9, no. 2, pp. 245–249, 2021.

[15] A. Verma and S. Jain, "Reward Point Systems as a Motivation Model in Donation-Based Applications," *Journal of Digital Innovations*, vol. 6, no. 1, pp. 39–44, 2020.

[16] R. Vats and H. Tiwari, "Application of MERN Stack in Real-Time Donation Platforms," in *International Conference on Advances in Computing and Communication Engineering (ICACCE)*, New Delhi, India, 2022, pp. 88–93, doi: 10.1109/ICACCE56740.2022.9842157.

[17] T. Saikia and K. Deka, "Transparency in Social Platforms Through Video Evidence: A Case Study on Donation Campaigns," *International Journal of Humanitarian Technology*, vol. 4, no. 3, pp. 112–117, 2021.

[18] M. Jain and S. Bhattacharya, "Leveraging MongoDB and Node.js for Real-Time Data-Driven Applications," *International Journal of Web Engineering*, vol. 10, no. 1, pp. 56–61, Jan. 2022.

[19] B. Johnson and K. Lee, "Food Sharing Economy Platforms: User Behavior and System Design," in *2021 IEEE Global Humanitarian Technology Conference (GHTC)*, Seattle, WA, USA, pp. 130–135, 2021, doi: 10.1109/GHTC53188.2021.9611421.

[20] P. Agarwal, "Smart Waste Management Using IoT and Donation Platforms," *International Journal of Engineering Research & Technology (IJERT)*, vol. 8, no. 7, pp. 23–27, July 2020.

[21] S. R. Kumar, "A Framework for Building Scalable Food Donation Systems," *IEEE Transactions on Sustainable Computing*, vol. 5, no. 4, pp. 490–498, Oct.–Dec. 2021, doi: 10.1109/TSUSC.2020.2976402.