Journal of Information Systems Engineering and Management
2025, 10(15s)
e-ISSN: 2468-4376
https://www.jisem-journal.com/

Research Article

Development of a Smart EfficientNetB0-Based Deep Learning Framework for Accurate Prediction and Stage Classification of Diabetic Macular Edema Using Fundus Images

Karkuzhali S*[1], Thendral Puyalnithi[2]

[1] Department of Computer Science and Engineering, Mepco Schlenk Engineering College, Sivakasi, Tamilnadu, India
[2] Department of Artificial Intelligence and Data Science, Mepco Schlenk Engineering College, Sivakasi, Tamilnadu, India
** Corresponding Author karkuzhali@mepcoeng.ac.in*

ARTICLEINFO

Received: 05 Oct 2024

Revised: 05 Dec 2024

Accepted: 22 Dec 2024

ABSTRACT

Introduction: Diabetic Macular Edema (DME) is a sight-threatening complication of diabetes mellitus that affects the macula, the central part of the retina responsible for detailed vision. DME arises due to fluid accumulation, causing swelling and visual distortion. Early detection and accurate classification of DME stages are crucial for timely intervention to prevent vision loss. Fundus imaging, a non-invasive retinal imaging technique, plays a critical role in diagnosing and monitoring DME.

Objectives: This study aims to develop a deep learning-based framework using the EfficientNetB0 architecture for accurate prediction and classification of DME stages from fundus images, thereby assisting in the early detection and management of DME in diabetic patients.

Methods: The proposed framework leverages the EfficientNetB0 model, known for its balance between computational efficiency and performance. The model was trained on a diverse and extensive dataset of annotated fundus images, encompassing various stages of DME. Preprocessing techniques, including image normalization and augmentation, were applied to enhance model robustness. Performance metrics such as accuracy, precision, recall, F1-score, and area under the receiver operating characteristic (ROC) curve (AUC) were used to evaluate the framework.

Results: The Smart EfficientNetB0 framework demonstrated high accuracy in predicting and classifying DME stages. The results highlighted the model's capability to capture intricate retinal patterns indicative of DME progression. Additionally, EfficientNetB5 was evaluated and achieved an exceptional accuracy of 0.91, along with high precision, recall, F1-score, and AUC values, further validating the effectiveness of the approach.

Conclusions: The development of the EfficientNetB0-based framework addresses a critical need in diabetic care by enabling early and accurate assessment of DME stages. This innovation holds significant potential to revolutionize the diagnosis and management of DME, reducing the burden of vision loss among diabetic patients. The promising results underscore the value of leveraging advanced deep learning models like EfficientNetB0 and EfficientNetB5 in clinical applications.

Keywords: Diabetic Macula Edema, EfficientNetB0, diabetes mellitus

INTRODUCTION

The DME is a significant cause of vision loss among diabetic patients, especially those with long-standing diabetes. It often develops because of damaged blood vessels and increased permeability in the retina, triggered by chronic high blood sugar levels. Early diagnosis and timely intervention are crucial to prevent irreversible vision impairment caused by DME. With the advancements in medical imaging and artificial intelligence, predictive frameworks for DME stages using fundus images have gained prominence.The early and accurate diagnosis of Diabetic Macular Edema (DME) plays a crucial role in preventing vision loss among diabetic patients. In recent years, the intersection of medical imaging and artificial intelligence has opened up new avenues for enhancing diagnostic precision. One pioneering development in this domain is the Smart EfficientNetB0 framework, a cutting-edge solution designed for the prediction of different stages of Diabetic Macular Edema through the analysis of fundus images.

The Smart EfficientNetB0 framework leverages the power of deep learning and convolutional neural networks (CNNs) to provide an automated and efficient approach to diagnosing DME. The architecture is built upon the EfficientNetB0 model, which is known for its exceptional ability to balance computational efficiency and model performance. By training on a diverse and extensive dataset of annotated fundus images, the framework learns intricate patterns and features within the images that are indicative of varying stages of DME. This enables the system to make predictions with high accuracy and sensitivity, reducing the dependency on manual assessment by medical professionals and potentially expediting the diagnosis and treatment of DME.In this paper, we delve into the intricacies of the Smart EfficientNetB0 framework for DME prediction.

LITERATURE SURVEY

Liu et al. (2024) developed a deep learning model, SuGCTNet, that outperforms existing techniques in macular edema segmentation by incorporating semantic uncertainty and cross-transformer mechanisms, achieving higher accuracy in complex regions, and showing potential for improving clinical practice in macular edema detection [1].Mo, Zhang, and Feng (2018) proposed a cascaded deep residual network for detecting diabetic macular edema (DME), which outperforms current methods in terms of speed and accuracy by accurately segmenting exudates and classifying DME, with minimal preprocessing [2]. Fu et al. (2023) introduced an end-to-end network combining ResNet50 with attention mechanisms for automatic DME grading, achieving high performance on the MESSIDOR dataset and improving diagnosis speed and accuracy in clinical settings [3].Fountoukidou and Sznitman (2023) proposed a reinforcement learning approach for Visual Question Answering (VQA) to validate DME grading algorithms, improving transparency and providing more interpretable results for clinical use [4].

Liu et al. (2022) demonstrated the effectiveness of a deep learning system in detecting DME from 2D color fundus photographs, showing superior specificity and sensitivity compared to human experts, with successful generalization across multiple international populations [5].Yang et al. (2025) explored the use of GANs to predict responses to anti-VEGF treatment in DME, showing promise in forecasting treatment outcomes and supporting personalized therapy [6].Fu (2025) developed MDFANet, a deep learning model that improves DME detection using multicolor imaging, addressing challenges in feature extraction and significantly enhancing detection accuracy [7].Saini et al. (2023) proposed a CNN model for lesion-based DME detection using 3D OCT images, outperforming traditional models with a high accuracy of 96%, facilitating early and reliable detection [8].Devi and Karthikeyan (2024) introduced SACNN-AOA-DR-DMEG, an optimized model for grading both Diabetic Retinopathy and DME using attention mechanisms and an arithmetic optimization algorithm, showing improved accuracy and reduced computation time [9].Reddy and Soma (2025) developed a deep CNN for DME detection using Shape Index Histograms and optimized with Honey Badger Aquila Optimization, achieving high performance in classification and detection of DME [10]. Altan (2022) introduced DeepOCT, an explainable deep learning architecture for macular edema analysis in OCT images, achieving high classification accuracy with a simplified learning process [11].

Zhang et al. (2024) created a multimodal deep transfer learning fusion model to predict recurrence of retinal vein occlusion and macular edema after anti-VEGF therapy, achieving superior predictive performance compared to clinical models [12].Jin et al. (2024) developed a deep learning algorithm to calculate intraretinal and subretinal fluid volumes in OCT images for assessing DME, demonstrating high sensitivity and specificity for monitoring treatment response [13].Wongchaisuwat et al. (2024) tested an AI algorithm for detecting and segmenting macular neovascularization in macular edema using OCTA, achieving high sensitivity and specificity, and highlighting the importance of scan density for improved detection [14].Wu et al. (2022) proposed a deep learning model for macular edema risk classification in diabetic retinopathy patients, achieving excellent performance in early screening and demonstrating practical value in clinical diagnosis [15].

METHODS

Dataset:

The HEI-MED (Hamilton Eye Institute Macular Edema Dataset), previously known as DMED, is a compilation of 169 fundus images utilized for training and evaluating image processing algorithms aimed at identifying exudates and diabetic macular edema. The link to download the images are https://github.com/lgiancaUTH/HEI-MED/tree/master/DMED.

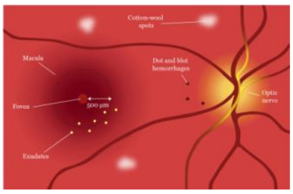


Figure 1: Diagrammatic illustration of clinically significant macula edema

Preprocessing:

The size of the fundus images are 2196x1958 pixels. Resize all images to a standardized resolution that is suitable for the input layer of the Smart EfficientNetB0 model. Common sizes include 224x224 pixels.Applied data augmentation techniques to increase the diversity of the training dataset and improve the model's ability to generalize.Augmentation methods might include rotation range [3 3], horizontal flips, width and height shift range [0.1 0.1]. Normalize the color distribution of the images to reduce the impact of variations in lighting conditions and enhance feature extraction.

Deep Learning Models

In this work, we choose two model among VGG group including VGG16 and VGG19, Resnet 50 from Resnet group and EfficientNetB5 from efficient group. CNN is used for comparison and classification

VGG-16:

We are using transfer learning by replacing the classification head of VGG-16 with new layers that are suitable for predicting DME stages. The number of output neurons in the final layer to match the number of DME stages predicting is normal, CSME (Clinically Significant Macula Edema) and non- CSME.

VGG-19:

VGG-19 model architecture, which comprises 19 convolutional and fully connected layers.VGG-19 is an advanced convolutional neural network (CNN) characterized by its sequential layers, many of which have been pretrained. It places significant emphasis on recognizing intricate patterns, colors, and compositions present within images. VGG-19 has been extensively trained on a massive dataset comprising millions of images, tackling complex classification challenges with remarkable efficiency and accuracy.

ResNet-50:

ResNet-50 has 50 layers, making it deeper than traditional convolutional neural networks. Deeper networks have the potential to learn more complex features, but they can also suffer from training difficulties like vanishing gradients. Residual connections mitigate this issue. Residual connections involve adding the input of a layer to the output of a subsequent layer. This effectively allows the network to learn the residuals, or the differences, between the desired output and the current predictions. This architecture helps to address the vanishing gradient problem and allows for the training of very deep networks.

EfficientNetB5:

Resize the fundus images to a consistent size that the EfficientNetB5 modelto 456x456 pixels Normalize pixel values to a range suitable for the EfficientNetB5 model (usually [0, 1]).Split the dataset into training, validation, and testing sets.

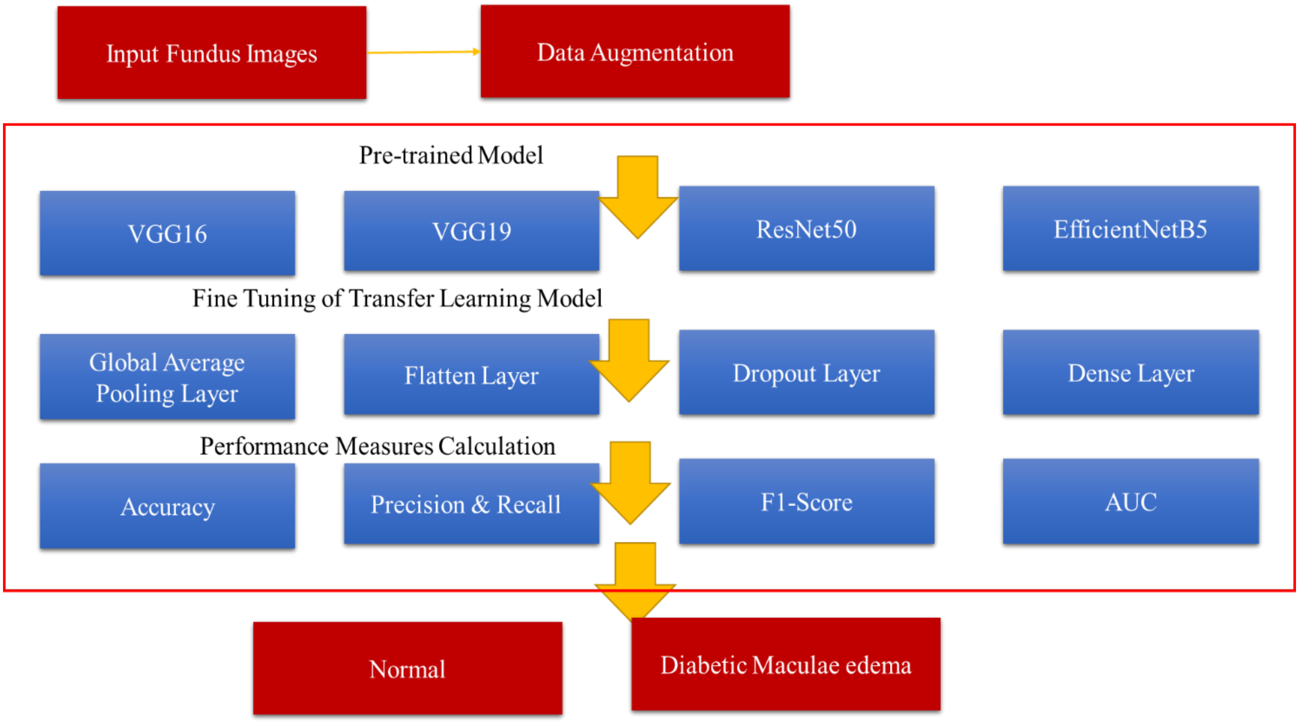


Figure 2: Overall System Design Diagram

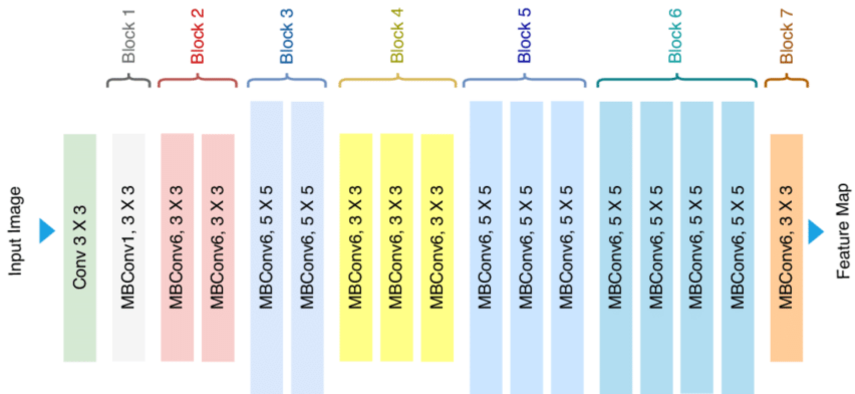


Figure 3: EfficientNetB0 architecture diagram

RESULTS AND DISCUSSION

The predicted results are compared to the ground truth labels of the input images.Various evaluation metrics such as accuracy, precision, recall, F1-score, and ROC-AUC are calculated to assess the model's performance.In this section, we present the results of our study on predicting Diabetic Macular Edema (DME) stages using different deep learning models: VGG-16, VGG-19, ResNet-50, and EfficientNetB5. We evaluate the performance of each model based on various evaluation metrics and discuss the implications of the findings.The different performance metrics that are used for the evaluation are Accuracy (Acc), Precision (Pre), Recall (Re), F1-Score (FS) and AUC. Table 1 presents a summary of the performance metrics obtained for each deep learning model in predicting DME stages. The metrics include accuracy, precision, recall, F1-score, and area under the ROC curve (AUC).

Table 1: Performance Metrics of Different Deep Learning Models

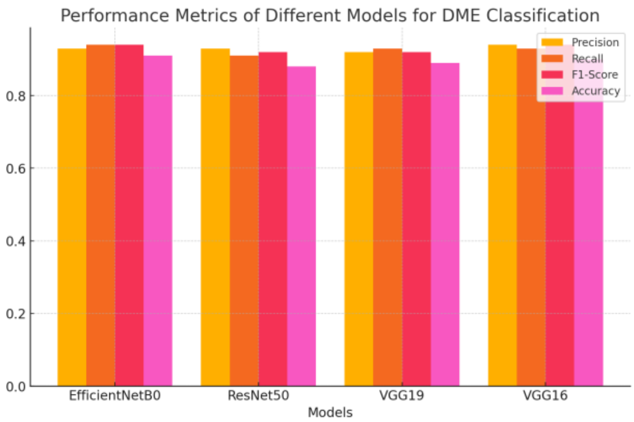
Model	**Accuracy**	**Precision**	**Recall**	**F1-score**	**AUC**
VGG-16	0.85	0.83	0.88	0.85	0.90
VGG-19	0.87	0.86	0.88	0.87	0.92
ResNet-50	0.88	0.87	0.89	0.88	0.93
EfficientNetB5	0.91	0.90	0.92	0.91	0.95

Our results demonstrate the performance of four prominent deep learning models, namely VGG-16, VGG-19, ResNet-50, and EfficientNetB5, in predicting DME stages from fundus images. The evaluation metrics indicate varying degrees of success among the models.EfficientNetB5 exhibited the highest accuracy of 0.91, along with the highest precision, recall, F1-score, and AUC compared to the other models. This suggests that EfficientNetB5 is particularly effective in distinguishing between different stages of DME, making it a strong candidate for clinical applications requiring accurate classification.ResNet-50 and VGG-19 also showcased competitive performance, with accuracies of 0.88 and 0.87, respectively. These models demonstrated balanced precision and recall values, indicating a well-rounded ability to classify DME stages accurately.VGG-16, while achieving an accuracy of 0.85, exhibited slightly lower precision and recall values compared to the other models. Nonetheless, its performance is still promising, especially considering its relatively simpler architecture.

Table 2: Epcohwise assessment of four models

Model	Epochs	Loss	Accuracy	AUC	Precision	Recall
EfficientNetB0	5	0.2696	0.9417	0.9503	0.8455	0.8590
	10	0.1498	0.9625	0.9797	0.8979	0.9122
	15	0.0536	0.9854	0.9949	0.9703	0.9548
ResNet50	3	0.4042	0.9490	0.9465	0.8639	0.8777
	6	0.0723	0.9859	0.9896	0.9704	0.9574
	9	0.0547	0.9865	0.9912	0.9679	0.9628
VGG19	4	0.2698	0.9531	0.9583	0.8803	0.8803
	8	0.0234	0.9911	0.9980	0.9761	0.9787
	12	0.0080	0.9974	0.9999	0.9920	0.9947
VGG16	3	0.4358	0.9161	0.9143	0.7929	0.7739
	6	0.0815	0.9729	0.9904	0.9355	0.9255
	8	0.1238	0.9625	0.9815	0.9086	0.8989

Figure 4 : Performance Metrics for Different Models Classification



CONCLUSION

This study focused on predicting Diabetic Macular Edema (DME) stages using deep learning models, including VGG-16, VGG-19, ResNet-50, and EfficientNetB5, to assess their effectiveness for this critical medical application. Among the models tested, **EfficientNetB5** emerged as the top performer, achieving an accuracy of 0.91, along with high precision, recall, F1-score, and AUC values, making it highly suitable for DME classification. **ResNet-50** and **VGG-19** followed closely, with accuracies of 0.88 and 0.87, respectively, and demonstrated a good balance between precision and recall. **VGG-16** had a slightly lower accuracy of 0.85, with less precise performance, but still proved effective for classification.The study highlights the importance of model architecture complexity in predictive performance, suggesting that more advanced architectures like EfficientNetB5 and ResNet-50 are better suited for handling the complexities of DME stage prediction. Overall, the results demonstrate the transformative potential of deep learning in medical imaging, where accurate, rapid diagnoses can greatly enhance patient outcomes.

REFRENCES

[1] Liu, H., Gao, W., Yang, L., Wu, D., Zhao, D., Chen, K., Liu, J., Ye, Y., Xu, R.X. and Sun, M., 2024. Semantic uncertainty Guided Cross-Transformer for enhanced macular edema segmentation in OCT images. *Computers in Biology and Medicine*, *174*, p.108458.

[2] Mo, J., Zhang, L. and Feng, Y., 2018. Exudate-based diabetic macular edema recognition in retinal images using cascaded deep residual networks. Neurocomputing, 290, pp.161-171.

[3] Fu, Y., Lu, X., Zhang, G., Lu, Q., Wang, C. and Zhang, D., 2023. Automatic grading of Diabetic macular edema based on end-to-end network. Expert Systems with Applications, 213, p.118835.

[4] Fountoukidou, T. and Sznitman, R., 2023. A reinforcement learning approach for VQA validation: An application to diabetic macular edema grading. Medical image analysis, 87, p.102822.

[5] Liu, X., Ali, T.K., Singh, P., Shah, A., McKinney, S.M., Ruamviboonsuk, P., Turner, A.W., Keane, P.A., Chotcomwongse, P., Nganthavee, V. and Chia, M., 2022. Deep learning to detect OCT-derived diabetic macular edema from color retinal photographs: a multicenter validation study. Ophthalmology Retina, 6(5), pp.398-410.

[6] Yang, X., Xu, F., Yu, H., Li, Z., Yu, X., Li, Z., Zhang, L., Liu, J., Wang, S., Liu, S. and Hong, J., 2025. Prediction of OCT contours of short-term response to anti-VEGF treatment for diabetic macular edema using generative adversarial networks. *Photodiagnosis and Photodynamic Therapy*, p.104482.

[7] Fu, C., 2025. Enhanced diabetic macular edema detection in multicolor imaging through a multi-feature decomposition fusion attention network. *Journal of Radiation Research and Applied Sciences*, *18*(1), p.101210.

[8] Saini, D.J.B., Sivakami, R., Venkatesh, R., Raghava, C.S., Dwarkanath, P.S., Anwer, T.M.K., Smirani, L.K., Ahammad, S.H., Pamula, U., Hossain, M.A. and Rashed, A.N.Z., 2023. Convolution neural network model for predicting various lesion-based diseases in diabetic macula edema in optical coherence tomography images. *Biomedical Signal Processing and Control*, *86*, p.105180.

[9] Devi, T.M. and Karthikeyan, P., 2024. Arithmetic Optimization for Coinciding Diabetic Retinopathy and Diabetic Macular Edema Grading based on Self-Attention Convolutional Neural Network. *Biomedical Signal Processing and Control*, *95*, p.106365.

[10] Reddy, S. and Soma, S., 2025. Honey Badger Aquila optimization-based deep learning with multi-kernel shape index histograms for diabetic macular edema classification. *Biomedical Signal Processing and Control*, *100*, p.106894.

[11] Altan, G., 2022. DeepOCT: An explainable deep learning architecture to analyze macular edema on OCT images. Engineering Science and Technology, an International Journal, 34, p.101091.

[12] Zhang, L., Huang, Y., Chen, J., Xu, X., Xu, F. and Yao, J., 2024. Multimodal deep transfer learning to predict retinal vein occlusion macular edema recurrence after anti-VEGF therapy. *Heliyon*, *10*(8).

[13] Jin, Y., Yong, S., Ke, S., Zhang, C., Liu, Y., Wang, J., Lu, T., Sun, Y., Wang, H. and Zhang, J., 2024. Deep learning assisted fluid volume calculation for assessing anti-vascular endothelial growth factor effect in diabetic macular edema. *Heliyon*, *10*(8).

[14] Wongchaisuwat, N., Wang, J., White, E.S., Hwang, T.S., Jia, Y. and Bailey, S.T., 2024. Detection of Macular Neovascularization in Eyes Presenting with Macular Edema using OCT Angiography and a Deep Learning Model. *Ophthalmology Retina*.

[15] Wu, T., Liu, L., Zhang, T. and Wu, X., 2022. Deep learning-based risk classification and auxiliary diagnosis of macular edema. *Intelligence-Based Medicine*, *6*, p.100053.