IAES International Journal of Artificial Intelligence (IJ-AI)
Vol. 14, No. 1, February 2025, pp. 54∼61
ISSN: 2252-8938, DOI: 10.11591/ijai.v14.i1.pp54-61

Predicting enhanced diagnostic models: deep learning for multi-label retinal disease classification

Sridhevi Sundararajan, Harikrishnan Ramachandran, Harshita Gupta, Yashraj Patil
Symbiosis Institute of Technology (SIT)-Pune Campus, Symbiosis International Deemed University (SIDU), Pune, India

Article Info

Article history:

Received Mar 29, 2024
Revised Jun 28, 2024
Accepted Jul 26, 2024

Keywords:

Classification
Deep learning
Medical imaging
Multi-label
Prediction models
Retinal disease

ABSTRACT

In this study, we assess three convolutional neural network (CNN) architectures—VGG16, ResNet50, and InceptionV3 for multi classification of fundus images in the retinal fundus multi-disease image dataset (RFMID2), comprising of 860 images. Focusing on diabetic retinopathy, exudation, and hemorrhagic retinopathy, we preprocessed the dataset for uniformity and balance. Using transfer learning, the models were adapted for feature extraction and fine-tuned to our multi-label classification task. Their performance was measured by subset accuracy, precision, recall, F1-score, hamming loss, and Jaccard score. VGG16 emerged as the top performer, with the highest subset accuracy (84.81%) and macro precision (95.83%), indicating its superior class distinction capabilities. ResNet50 showed commendable accuracy (79.75%) and precision (86.70%), whereas InceptionV3 lagged with lower accuracy (66.67%) and precision (81.21%). These findings suggest VGG16's depth offers advantages in multi-label classification, highlighting InceptionV3's limitations in complex scenarios. This analysis helps optimize CNN architecture selection for specific tasks, suggesting future exploration of dataset variability, ensemble methods, and hybrid models for improved performance.

Corresponding Author:

Harikrishnan Ramachandran
Symbiosis Institute of Technology (SIT)-Pune Campus, Symbiosis International Deemed University (SIDU)
Pune 412115, India
Email: harikrishnan.r@sitpune.edu.in

1. INTRODUCTION

The integration of AI-driven image processing in healthcare has marked a significant leap forward in diagnosing critical retinal conditions such as diabetic retinopathy [1], exudation [2], and hemorrhagic retinopathy [3]. These conditions, notorious for their potential to impair vision, are increasingly being detected with advanced computational approaches, notably convolutional neural networks (CNNs) [4]. Our investigation evaluates the capabilities of three distinguished CNN models— VGG16 [5] , ResNet50 [6], and InceptionV3 [7]—on the retinal fundus multi-disease image dataset (RFMID2) dataset [8], which encompasses 860 fundus images annotated for these specific diseases. The generation of the dataset RFMID2 is depicted in Figure 1. Applying transfer learning [9] followed by feature extraction [10] of the fundal images, we aim to fine-tune these models to the task of multi-label retinal disease classification. The RFMID2 dataset serves as an ideal ground for this exploration, given its diverse and comprehensive annotation of retinal pathologies. By ensuring a balanced dataset and employing rigorous preprocessing measures, we seek to establish a level field for evaluating model performance across key metrics [11]: subset accuracy, precision, recall, F1 score, hamming loss, and Jaccard score [12]. As the global incidence of retinal diseases escalates, the urgency for developing rapid and reliable diagnostic tools becomes paramount. This study not only compares the effectiveness of different CNN architectures in automated retinal disease detection but also aims to contribute to the enhancement of diagnostic processes in ophthalmology. Through our findings, we anticipate setting the stage for future advancements in automated retinal imaging [13], potentially transforming patient care and management in the field.

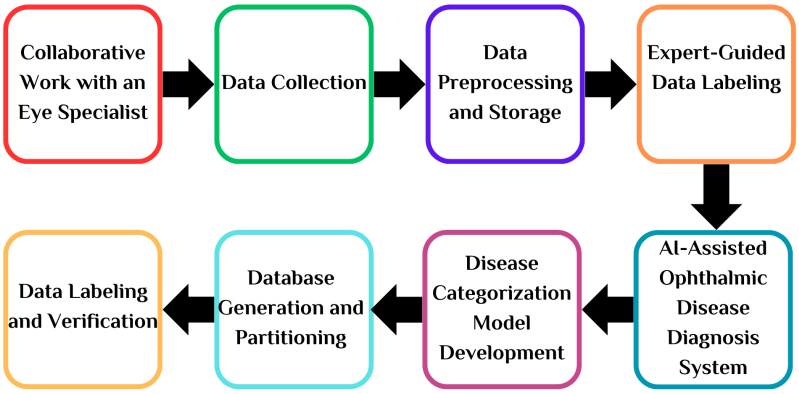

Figure 1. Creation of retinal fundus multi image dataset RFMID2 [8]

The advent of CNNs has significantly impacted machine learning [14], enhancing multi-label classification [15] tasks across various domains, including medical image analysis [16]. VGG16, ResNet, and Inception are notable architectures that have contributed to advancements in this field. VGG16 is celebrated for its depth and the use of small, uniform filters, making it adept at capturing detailed features crucial for medical imaging. Its architectural simplicity has played a pivotal role in deepening our understanding of CNNs. ResNet introduces skip connections, allowing the training of very deep networks by overcoming the vanishing gradient problem. This innovation enables the learning of complex patterns, illustrating the model's versatility in tasks such as disease classification from medical scans. Inception models, with their unique inception modules, capture information at different scales. This capability is particularly beneficial for medical diagnostics, where images may contain intricate patterns across various resolutions. Applying these CNNs in medical imaging has transformed diagnostic methods, enabling the classification and diagnosis of multiple diseases from a single image with unprecedented accuracy. This advancement not only simplifies the diagnostic process but also improves early disease detection, potentially enhancing patient outcomes. The continuous evolution of CNN architectures promises further advancements in medical image analysis. VGG16, ResNet, and Inception models, with their versatility and adaptability, promise a future where AI-driven diagnostics combined with human expertise, offering faster and more precise diagnoses. Table 1 describes the a brief review on the deep learning techniques for retinal diseases classification.

In the exploration of CNNs for retinal disease classification using datasets like RFMID2, researchers face a set of challenges but also encounter numerous opportunities for advancement. Understanding these can guide future research directions and help in overcoming existing limitations. The Table 2 explains the challenges and opportunities in retinal disease classification right from data collection till diagnosis.

The advent of deep learning has revolutionized the field of medical imaging, offering unprecedented opportunities for enhancing diagnostic accuracy and patient care. CNNs, in particular, have shown remarkable success in automatically detecting and classifying diseases from various types of medical images. This potential is especially pertinent in the realm of ophthalmology, where conditions like diabetic retinopathy, exudation, and hemorrhagic retinopathy can be identified through retinal imaging. Timely and precise detection of these diseases is vital to prevent severe consequences, such as blindness. Thus, leveraging deep learning for this purpose addresses a significant need in healthcare. In light of these developments, this work proposes to apply and compare three state-of-the-art CNN architectures—VGG16, InceptionV3, and ResNet50—for the classification of ophthalmic diseases in retinal images. By leveraging these models' pre-trained weights for feature extraction and employing custom classification layers, this study aims to investigate each architecture's efficacy in accurately identifying diabetic retinopathy, exudation, and hemorrhagic retinopathy. This comparative analysis will contribute to identifying the most suitable deep learning approach for enhancing diagnostic processes in ophthalmology, ultimately aiding in early disease detection and treatment planning. The Table 3 explains the techniques and analysis done for this research.

Table 1. Review on deep learning approaches in retinal disease classification

Topic	Description
Multilevel glowworm swarm optimization convolutional neural network (MGSCNN) [17] for multi-disease classification	A method that integrates CNN with glowworm swarm optimization (GSO) [18] for classifier optimization, emphasizing normalization, smoothing, and resizing in preprocessing. This model showcases the efficacy in enhancing classification accuracy for retinal images.
Addressing class imbalance [19]	The literature provides various strategies to handle class imbalance problems. These strategies include resampling methods (both oversampling minority classes and undersampling majority ones), classifier adaptation that requires the model to be tailored to address the dataset's imbalance, ensemble approaches that use multiple models, and cost-sensitive methods that employ custom metrics in the loss function to emphasize the minority classes.
Optical coherence tomography (OCT) image classification with VGG-16 [20]	Describes the adaptation of VGG-16 using transfer learning for OCT retinal images, focusing on data augmentation and custom layers for disease classification. Includes performance evaluation metrics and Grad-CAM for model visualization [21].
Publicly available fundus image datasets [22]	A variety of datasets have been reviewed and are used in multi-label retinal disease classification, including DRIVE, STARE, CHASE-DB, Messidor, and e-ophtha datasets. Each dataset has been developed for different diagnostic purposes, exhibiting diverse variations and abnormalities that are crucial for training deep learning models.

Table 2. From data to diagnosis: artificial intelligence challenges and opportunities in retinal disease classification

Challenges	Opportunities
Class imbalance: A common issue in medical datasets, including those for retinal diseases, is class imbalance. Minority classes (rarer diseases) are not much in number, which can bias the model towards more frequent conditions. Addressing this requires innovative strategies beyond simple resampling, demanding more sophisticated approaches like cost-sensitive learning or synthetic data generation.	Advanced architectural innovations [23]: Exploring beyond VGG16, ResNet, and Inception models to newer architectures can provide opportunities for improved performance. Innovations in neural network design could offer solutions to class imbalance, enhance feature extraction, and improve model interpretability.
Data quality and variability: The quality of retinal images can vary significantly due to different imaging conditions, patient demographics, and disease stages. This variability can hinder the model's ability to generalize from the training data to real-world applications.	Multi-modal data fusion [24]: Combining retinal fundus images with other types of medical data (e.g., OCT [25], patient demographics) through multi-modal learning approaches could enhance diagnostic accuracy and offer a more holistic view of patient health.
Interpretability and trust: For clinical applications, it's crucial that model predictions are interpretable by healthcare professionals. Developing models that offer transparency in their decision-making process remains a challenge, affecting their adoption in clinical settings.	Transfer learning and domain adaptation [26]: Leveraging transfer learning more effectively, including domain adaptation techniques, can help models better generalize across different datasets and imaging conditions, reducing the gap between research settings and real-world applications.
Integration with clinical workflows: Successfully integrating AI models into clinical workflows involves challenges related to system compatibility, data privacy, and the need for real-time analysis without disrupting existing procedures.	Collaboration between AI researchers and clinicians: Strengthening the collaboration between AI researchers and clinical practitioners can lead to the development of more practical, user-friendly AI tools that fit seamlessly into clinical workflows and address real healthcare needs.

The study explores the impact of architectural variations inherent to VGG16, inceptionV3, and ResNet-50. This includes the depth of the networks, the use of inception modules versus residual connections, and their implications for feature representation and extraction capabilities. Each model was fine-tuned to the specific task of medical image classification. This involved adjusting learning rates, experimenting with different numbers of dense layers in the classification head, and exploring dropout for regularization to prevent overfitting.

Table 3. CNN architectures in ophthalmic disease detection: techniques, variations, and insights

Methodology/feature extraction	Description
Dataset description	The study uses a RFMID2 consisting of 860 images labeled with the presence or absence of diabetic retinopathy, edema, and hemorrhagic retinopathy. The labels are encoded in a CSV file, facilitating a structured approach to supervised learning.
Balancing and sampling	To address potential class imbalance, a balanced subset of images was constructed. This ensures equitable representation of each condition, enhancing the model's ability to learn from an evenly distributed dataset.
Image resizing and normalization	All images were resized to 512x512 pixels to standardize input size. Additionally, pixel values were normalized to a [0, 1] range to aid in model convergence and efficiency during training.
Data analysis	The comparative analysis of label frequencies and combinations was conducted for both retinal fundus multi image datasets that includes creating graphical representations to illustrate label frequencies and co-occurrence patterns
Utilization of pre-trained models	Leveraging the VGG16, InceptionV3, and ResNet50 models pre-trained on ImageNet enables the extraction of rich, hierarchical features from the medical images, even with a limited dataset size.
Global average pooling (GAP)	Following feature extraction, a GAP layer was applied to reduce the feature dimensionality while maintaining spatial hierarchies, facilitating a robust input for the classification layer.

2. METHOD

This section thoroughly outlines the methods adopted in our investigation. It details the research framework, the procedures for obtaining the dataset, and the analytical strategies applied to fulfill our investigative goals. We offer an in-depth description of our procedural approach to maintain openness and ensure a clear understanding of our research execution.

2.1. Setup and variables considered

The Table 4 describes the specification of the retinal fundus dataset used in the research. The RFMID2 [8] a publicly accessible dataset has 860 retinal images, respectively. From this diabetic retinopathy, exudation, and hemorrhagic retinopathy have been identified for this reserach.

Table 4. Specification of the retinas fundus dataset [8]

Aspect	Desciption of the medical data
Research domain	Multiple label classification of retinal fundus image
Detailed study focus	Classification of various diseases using retinal fundus images
Collection method	Utilized the TOPCON TRC-NW300 for data collection
Data presentation	Includes images and associated data in CSV format
Variables under study	The majority of the subjects underwent mydriasis dilation using 0.5% tropicamide. Another subsect of patients without mydriasis were also accessed.
Experimental setup	Images captured using non-invasive techniques, maintaining specific distances between the camera lenses and the subjects' eyes with the patients in a seated position.
Data origin	Data collected from Shri Ganpati Netralaya in Jalna, Maharashtra, and the Center of Excellence in Signal and Image Processing at SGGS Institute of Engineering and Technology in Nanded, Maharashtra, India.

2.2. Dataset processing

The Figure 2 depicts the flowchart explaining the methodology used in this research for the classification of retinal diseases from RFMID2 dataset. The methodology depicted in the flowchart explains the use of convolutional neutal networks for the classification of retinal images. It starts with identifying the labels that are crucial for this study namely diabetic retinopathy, exudation, and hemorrhagic retinopathy from the 860 fundus images. Starting with data collection, the algorithm follows the integration of fundal images and the disease labels to ensure preprocessing steps like resizing, normalization, and dataset partitioning. This faciliates the model training and validation. An emphasis is specifically placed on the dataset imbalance to ensure an unbiased model evaluation. This research study has considered three CNN architectures namely VGG16, InceptionV3, and ResNet50 for the feature extraction of the fundal images. GAP is implemented to simplify the complex data from the images into a format that is easier to identify the patterns assosiated with the retinal diseases used in this study. Training is conducted followed by evaluation of the model's prediction against the established performance metrics. This way of structured comaparison and analysis of the results highlights the efficiency of the models in diagnosisng retinal diseases. The prediction also helps shed light into the details surronding diabetic retinopathy, exudation, and hemorrhagic retinopathy. With this rigorous process the research helps to identify the promising CNN architecture for fundal images, therby offering valuable insights into the automated diagnosis of retinal conditions to help in advance opthalmic cure.

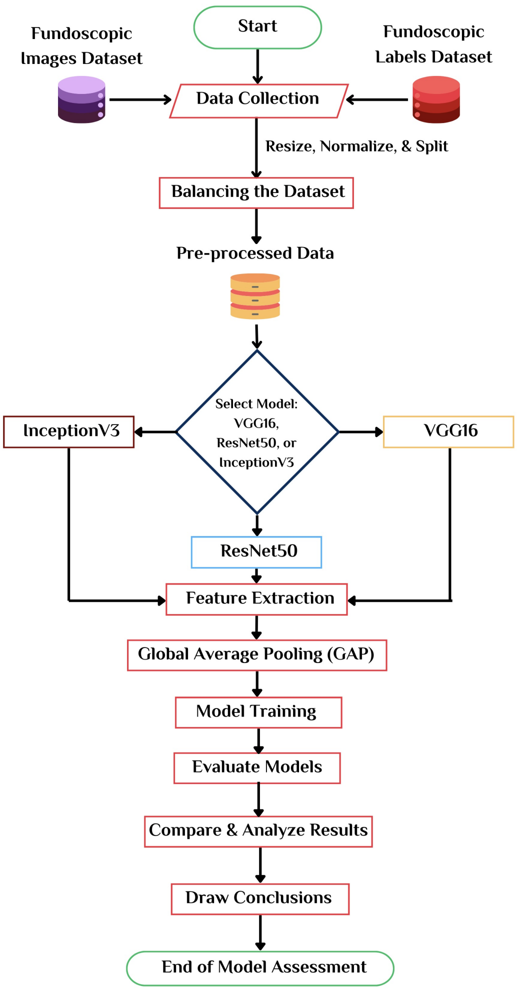

Figure 2. Flowchart for deep learning in ophthalmic disease classifications

3. RESULTS AND DISCUSSION

Based on the comparison of the three architectures considered in the research we have arrived at the following analysis which reveals the distinct performance features of VGG16, InceptionV3, and ResNet models, highlighting their use in various applications based on their unique strength and weakness. The VGG16 model demonstrates superior performance in almost all evaluated metrics. With a subset accuracy of 84.81%, it significantly outperforms Inception and ResNet models in predicting the entire set of labels for an instance. This is complemented by its high precision, both on a macro (95.83%) and micro (95.56%) level, suggesting that the model is particularly effective at minimizing false positives. Moreover, VGG16's recall rates (macro: 80.74%, micro: 79.63%) gives a strong indication about its capability to identify positive instances, which, combined with its precision, leads to the highest F1-scores among the models (macro: 87.22%, micro: 86.87%). These results highlight VGG16's balanced performance, making it a robust choice for tasks requiring precise label predictions. ResNet, on the other hand, presents itself as a competitive alternative, with a subset accuracy of 79.75%, positioning it between VGG16 and Inception in terms of the ability to match the full label set. While its precision and recall scores are moderately lower than those of VGG16, they still showcase respectable performance (precision macro: 86.70%, recall macro: 75.37%). The F1-scores for ResNet (macro: 80.00%, micro: 79.21%) further underscore its balanced precision-recall trade-off, indicating its effectiveness in a variety of scenarios where a slightly lower accuracy is acceptable. Inception's performance, while trailing behind VGG16 and ResNet, offers insights into the challenges and limitations of the architecture within the specific task context. With a subset accuracy of 66.67%, and the lowest precision (macro: 81.21%, micro: 78.05%) and recall (macro: 59.72%, micro: 60.38%) scores among the three, Inception appears to struggle more with correctly identifying positive instances and minimizing false positives. Its F1-scores (macro: 65.51%, micro: 68.09%) reflect these challenges, suggesting areas for improvement, particularly in tasks requiring high precision and recall. The Table 5 shows the results of the three CNN architecture models namely VGG16, Inception, and ResNet models carried out in this research study.

Table 5. Comparative analysis of VGG16, Inception, and ResNet across key performance indicators

Metrics	VGG16 (%)	Inception (%)	ResNet (%)
Subset accuracy	84.81	66.67	79.75
Precision (Macro)	95.83	81.21	86.70
Recall (Macro)	80.74	59.72	75.37
F1-Score (Macro)	87.22	65.51	80.00
Precision (Micro)	95.56	78.05	85.11
Recall (Micro)	79.63	60.38	74.07
F1-Score (Micro)	86.87	68.09	79.21
Hamming Loss	5.49	12.82	8.86
Jaccard Score (Macro)	78.62	53.10	69.30
Jaccard Score (Micro)	76.79	51.61	65.57

The graph represented in Figure 3 gives an overview between the performance metrics of the VGG16, Inception, and ResNet models across the key metric as discussed in the Table 5. We see that VGG16 emerges as the most accurate and balanced model, offering high precision and recall, which are critical for applications demanding stringent accuracy in label prediction. ResNet's performance, while not reaching the heights of VGG16, remains strong, suggesting its potential as a versatile model capable of delivering robust results across various tasks. Inception's lower performance metrics indicate potential difficulties in tasks requiring high precision and recall, highlighting the importance of model selection based on specific task requirements and the inherent trade-offs between different architectures. This comparison not only emphasizes the strengths of VGG16 in achieving high accuracy and a balanced precision-recall relationship but also illustrates the versatility of ResNet and the targeted applicability of Inception. The choice between these models should be guided by the specific requirements of the application, including the need for precision, recall, and the ability to correctly predict complete sets of labels.

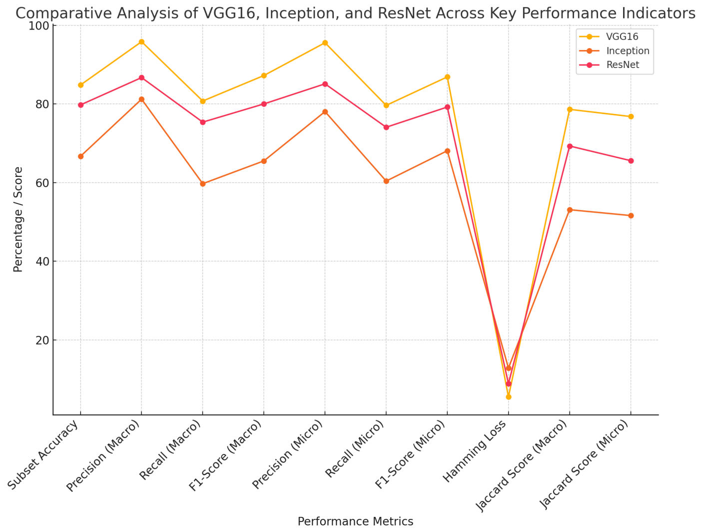

Figure 3. Grouped bar depicting the comparative analysis of VGG16, Inception, and ResNet across key performance indicators

4. CONCLUSION

This study's findings underscore the importance of model selection in the deployment of CNNs for image recognition tasks. The choice of model can significantly influence the outcome, depending on the specific requirements of accuracy, computational efficiency, and application context. Future research should explore the adaptability of these models to emerging image recognition challenges, including their performance on increasingly complex datasets and in real-world scenarios. Additionally, investigating the integration of these architectures into ensemble methods could offer paths to further enhance their accuracy and efficiency. In conclusion, while VGG16 emerges as the top performer in our analysis, the strengths of ResNet and Inception in certain contexts cannot be overlooked. The decision to employ a particular model should be guided by the specific demands of the task at hand, balancing considerations of accuracy, efficiency, and practical constraints. As the field of deep learning continues to evolve, so too will the capabilities and applications of these models, promising new opportunities for innovation and improvement.

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BIOGRAPHIES OF AUTHORS

Sridhevi Sundararajan is actively engaged in her postgraduate studies, pursuing a Master of Technology in Engineering Design at Symbiosis Institute of Technology in Pune, India. She has around 15 years of experience in IT domain with C++, Unix being her main forte. Her area of interest is research in medical domain. She likes to spend her time reading books related to medical field and exploring unknown. She can be contacted at email: sridevisundarajan@gmail.com.

Harikrishnan Ramachandran is currently working as associate professor in the Department of Electronics and Telecommunication Engineering, Symbiosis Institute of Technology, Pune Campus, Symbiosis International Deemed University, Pune, India. His main research interest includes smart grid, optimization, internet of things, artificial intelligence, and data analytics. He is an IEEE senior member, fellow life member of Institution of Engineers India, fellow life member of IETE India, life member of Indian Society for Technical Education and life member of Computer Society of India. He can be contacted at email: dr.rhareish@gmail.com.

Harshita Gupta is currently in the final year of her bachelor's degree in Electronics and Telecommunication Engineering from Symbiosis Institute of Technology, Pune, Symbiosis International Deemed University. Additionally, she is pursuing a minor in Data Science from the Department of Computer Science of the same university. With a keen interest in the dynamic fields of artificial intelligence, machine learning, deep learning, and computer vision, she is poised to contribute to the future of technology. She can be contacted at email: harshitag2810@gmail.com.

Yashraj Patil is a final year research scholar at Symbiosis Institute of Technology, Pune Campus, Symbiosis International Deemed University, Pune, India, pursuing a Master of Technology in Engineering Design. His main research interest includes internet of things, artificial intelligence, data analytics, and earth and space science. He is a UNITAR Global Diplomacy Fellow, distinguished speaker at UN General Assembly Science Summit, GLOBE Scientist at the NASA's GLOBE Program and a peer mentor in NASA's SEES Summer Internship Program. He can be contacted at email: yashrajpatil2798@gmail.com.