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Iris-based lung cancer pre-scanning for mobile platforms

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ABSTRACT

Lung cancer remains one of the leading causes of cancer-related mortality globally, with early detection being critical for improving survival rates. Traditional diagnostic methods such as computed tomography (CT) scans and biopsies are effective but often costly, invasive, and inaccessible in resource-limited settings. In this study, we evaluate suitable deep learning models for mobile platforms and propose an application for early detection of lung cancer based on iris images. Through experimentation and comparison, the results show that the MobileNet model family achieves high performance while maintaining a light-weight architecture. The positive results of this study further strengthen the potential application of iris in the pre-diagnosis of lung cancer via mobile platforms.

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1. INTRODUCTION

Lung cancer continues to be one of the most prevalent and lethal forms of cancer worldwide, accounting for approximately 1.8 million deaths annually [1]. Early detection is paramount in improving survival rates, as five-year survival decreases dramatically from 59% for localized disease to just 6% for metastatic cases [2]. Current diagnostic techniques, including computed tomography (CT) scans, positron emission tomography (PET) scans, and biopsies, while effective, present significant barriers including high costs, radiation exposure, invasiveness, and limited accessibility in resource-constrained environments [3]-[6]. These limitations underscore the urgent need for alternative, accessible, and non-invasive screening methods.

The human iris has emerged as a promising area in medical research due to its potential to reflect systemic health conditions [7]-[9]. Iridology, the study of iris patterns for health assessment, suggests that physiological and pathological conditions can manifest as detectable changes in iris characteristics. This connection forms the foundation for an emerging research domain investigating correlations between ocular features and internal health conditions. With the proliferation of high-resolution iris imaging technology in modern mobile devices, there is tremendous potential for widespread, accessible medical applications. Research in ophthalmology has demonstrated that the iris may represent systemic health issues such as diabetes, neurological illnesses, and cardiovascular ailments [10]. A promising option for non-invasive screening, studies have indicated that some iris anomalies may correlate with underlying illnesses.

Deep learning has revolutionized the field of clinical imaging by enabling automated, accurate, and scalable analysis of complex medical data. Convolutional neural networks (CNNs), in particular, have demonstrated exceptional performance in image classification, segmentation, and detection tasks across a variety of imaging modalities, including magnetic resonance imaging (MRI), CT, X-rays, and fundus

photography. These models are capable of learning hierarchical features directly from raw pixel data, eliminating the need for handcrafted feature extraction and significantly improving diagnostic accuracy. In radiology and pathology, deep learning systems have achieved performance comparable to or even surpassing that of experienced clinicians in detecting diseases such as cancer, diabetic retinopathy, and pneumonia. For instance, Esteva *et al.* [11] trained a CNN on a large dataset of skin lesion images and achieved dermatologist-level accuracy in classifying malignant melanoma. Similarly, Gulshan *et al.* [12] developed a deep learning algorithm for diabetic retinopathy detection using retinal fundus images, achieving high sensitivity and specificity comparable to board-certified ophthalmologists. Moreover, deep learning has shown promise in the early detection of pulmonary diseases; Rajpurkar *et al.* [13] introduced CheXNet, a 121-layer CNN that outperformed radiologists in identifying pneumonia on chest X-rays. These innovations facilitate faster image processing, support early diagnosis, and enable real-time clinical decision-making. Despite these advances, the clinical deployment of deep learning models still faces challenges related to data privacy, model interpretability, generalization across diverse populations, and regulatory approval. Addressing these issues is essential for integrating deep learning systems into routine clinical workflows and ensuring their safe and equitable use in healthcare.

The integration of iris scanners into mobile phones represents a significant advancement in biometric authentication, offering a secure and user-friendly alternative to traditional methods such as PINs or fingerprint sensors. Iris recognition is particularly valued for its high level of accuracy, given that the iris pattern is unique for every individual and remains stable over time. This technology operates by capturing an image of the user's iris using near-infrared light and matching it against stored templates for verification. One of the key advantages of iris scanning is its resilience to spoofing, as replicating the intricate texture of an iris is considerably more difficult than forging fingerprints. Additionally, iris recognition systems can function effectively in various lighting conditions and do not require direct contact, enhancing hygiene and user convenience. The deployment of iris scanners in smartphones, such as in the Samsung Galaxy Note 7 and S8, has demonstrated the feasibility of miniaturizing and integrating this technology into consumer electronics [14].

This study proposes an approach for lung cancer pre-screening based on iris pattern analysis using advanced deep learning techniques. Deep learning has revolutionized medical diagnostics through its capacity for automated feature extraction, classification, and predictive analysis. By leveraging state-of-the-art neural network architectures, this study aims to develop a robust and accurate screening tool capable of distinguishing lung cancer patients from healthy individuals based on iris images.

2. METHOD

2.1. Dataset

This study utilized a comprehensive dataset of high-resolution iris images, comprising 7,990 samples (3,494 positive samples from lung cancer patients and 4,496 negative samples from healthy individuals). Each image was captured using standardized protocols to ensure consistency in lighting, angle, and resolution. The structure of the dataset is presented in Figure 1.

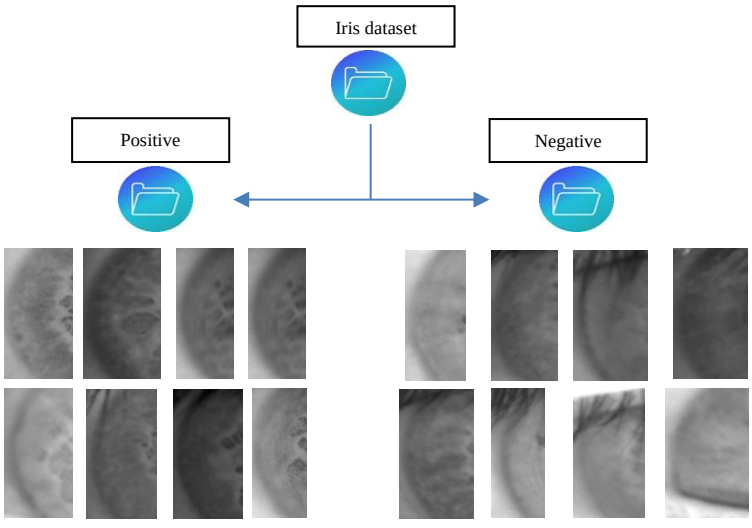

Figure 1. The structure of iris dataset

2.2. Deep learning models for mobile application

The deployment of deep learning models on mobile devices requires lightweight architectures that balance predictive performance with computational efficiency. To address the limitations of mobile hardware, several optimized neural network models have been developed. Notably, MobileNet (architecture described in Figure 2) and its variants are among the most widely adopted architectures for mobile and embedded systems due to their compact size and efficient depthwise separable convolutions, which significantly reduce the number of parameters and floating-point operations [15], [16]. In this study, we conduct experiments based on the iris dataset to evaluate the MobileNet and MobileNetV2 models compared with models with more parameters than they are, such as ResNet101V2 and ResNet152V2.

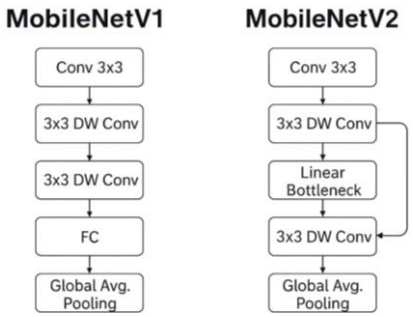

Figure 2. Architecture of MobileNet and MobileNetV2

2.3. Deep learning in medical diagnostics

Deep learning applications in medical imaging have shown remarkable success across various diagnostic domains [17]. CNNs have demonstrated particular effectiveness in detecting cancerous lesions from radiological images, with studies reporting accuracy rates exceeding 90% [18]. However, research leveraging alternative, non-traditional imaging sources like iris patterns for disease diagnosis remains limited.

Ophthalmic research has highlighted the potential of the iris in reflecting systemic health conditions [19]. Studies have suggested that specific iris abnormalities may correlate with underlying pathologies, making it a promising candidate for non-invasive screening.

Several studies have explored machine learning models for biomedical image classification, including support vector machines (SVM), random forest, and various deep learning architectures [20]. Cheung *et al.* [21] recently applied deep learning models to retinal images for early detection of Alzheimer's disease, achieving 83.6% accuracy. Banowati *et al.* [22] proposed using CNN to pre-diagnose high cholesterol based on iris images. In another study, Avhad and Bakal [23] used deep learning to develop a prediagnostic model for diabetes based on iris images. Our study extends this work by investigating the feasibility of using iris-based biomarkers as an alternative screening approach specifically for lung cancer detection.

2.4. Implementation

We employed transfer learning using multiple state-of-the-art CNN architectures pre-trained on the ImageNet dataset. This approach leverages the feature extraction capabilities of models trained on millions of diverse images while adapting them to our specific medical application.

For each model, we implemented a custom architectural adaptation:

a. The base model was loaded with ImageNet pre-trained weights
b. The original classification head was removed
c. A custom classification head was added, consisting of:

- Global average pooling layer,
- Dropout layer (0.5) for regularization,
- Dense layer with 512 units and ReLU activation,
- Batch normalization layer,
- Final dense layer with sigmoid activation for binary classification.

The dataset was split into training (80%) and validation (20%) sets, with stratification to maintain class distribution. All experiments were con-ducted on a system with Intel Core i5-10400F CPU, 16 GB RAM, and NVIDIA GeForce GTX 1050 Ti GPU using TensorFlow 2.6 and Keras.

3. RESULTS AND DISCUSSION

Given the medical nature of this application, we evaluated model performance using multiple metrics with particular emphasis on recall (sensitivity) and precision to assess the models' capability to correctly identify positive cases while minimizing false positives:

- Recall/sensitivity: the proportion of actual positive cases correctly identified (critical for screening applications).
- Precision: the proportion of positive identifications that were actually correct.
- F1-score: the harmonic mean of precision and recall.

Table 1 presents the performance metrics of deep learning models: ResNet101V2, ResNet152V2, MobileNet, and MobileNetV2. The confusion matrices of the models are presented in Figure 3.

Table 1. The performance of deep learning models

Model	Accuracy (%)	Precision (%)	Recall (%)	F1-score	Response time (ms)
ResNet101V2	93.33	93.66	86.29	0.8982	623
ResNet152V2	93.02	94.92	84.04	0.8915	604
MobileNet	93.48	93.69	86.74	0.9008	603
MobileNetV2	93.56	93.29	87.42	0.9026	596

In the comparative evaluation of four deep learning models - ResNet101V2 (Figure 3(a)), ResNet152V2 (Figure 3(b)), MobileNet (Figure 3(c)), and MobileNetV2 (Figure 3(d)) - across standard classification metrics, MobileNetV2 demonstrated the highest overall performance. The analysis considered accuracy, precision, recall, and F1-score, which collectively provide a holistic view of each model's predictive capabilities. MobileNetV2 achieved the highest accuracy (93.56%), indicating it correctly predicted the highest proportion of all samples. Additionally, it attained the highest recall (87.42%). The F1-score, a balanced metric combining precision and recall, was also highest for MobileNetV2 at 0.9026. This suggests a strong trade-off between precision and recall, making MobileNetV2 the most reliable model among those evaluated.

Figure 3. Confusion matrices of models; (a) ResNet101V2, (b) ResNet152V2, (c) MobileNet, and (d) MobileNetV2

MobileNetV2 demonstrates the highest performance with the lowest false negative rate, recording only 56 missed positive cases out of 445 actual positive instances, resulting in a sensitivity of 87.5% and a miss rate of merely 12.5%. MobileNet exhibits comparable performance with 59 false negatives (sensitivity: 86.7% and miss rate: 13.3%), while ResNet101V2 shows moderate effectiveness with 61 false negatives (sensitivity: 86.3% and miss rate: 13.7%). ResNet152V2 presents concerning results with 71 false negatives,

translating to a substantially elevated miss rate of 16% and a sensitivity of only 84 %. In the context of medical diagnosis, particularly for lung cancer pre-screening applications, the clinical implications of false negatives are paramount, as undetected cases can lead to delayed treatment and adverse patient outcomes. The highest performance of MobileNetV2, combined with its inherent computational efficiency for mobile deployment, positions it as the optimal choice for this application. However, in future work, we will apply data processing techniques to enrich the dataset, collect more primary data sources to cover more cases, and increase the efficiency of the model.

MobileNetV2 showed balanced results with an accuracy of 93.56%, precision of 93.29%, and recall of 87.42%, leading to an F1-score of 0.9026. While not the highest in any individual metric, its consistent performance across all metrics suggests it is a stable model choice when neither high recall nor high precision is a strict priority. On the other hand, MobileNet, the lightest model in the group, achieved a comparative performance: accuracy: 93.48%, precision: 93.69%, recall: 86.75%, and F1-score: 0.9008. MobileNetV2 and MobileNet have lightweight architectures and may still be viable candidates for deployment in resource-constrained environments.

MobileNetV2 achieves the fastest inference time at 596 ms, followed closely by ResNet152V2 (604 ms), MobileNet (603 ms), and ResNet101V2 (623 ms) while traditional approaches such as CT require a waiting time much longer [24].

In conclusion, MobileNetV2 Figures 4(a) to (d) show the comparision among models in term of accuracy, precision, recall, F1-score; respectively) outperformed the other models in all considered metrics and demonstrated a strong balance between precision and recall, making it the most suitable choice for high-performance classification tasks. ResNet152V2 could be preferred in scenarios demanding higher recall, whereas MobileNet might be optimal for applications with limited computational resources. In addition, we will also try explanable AI approaches to increase the persuasiveness of the models [25].

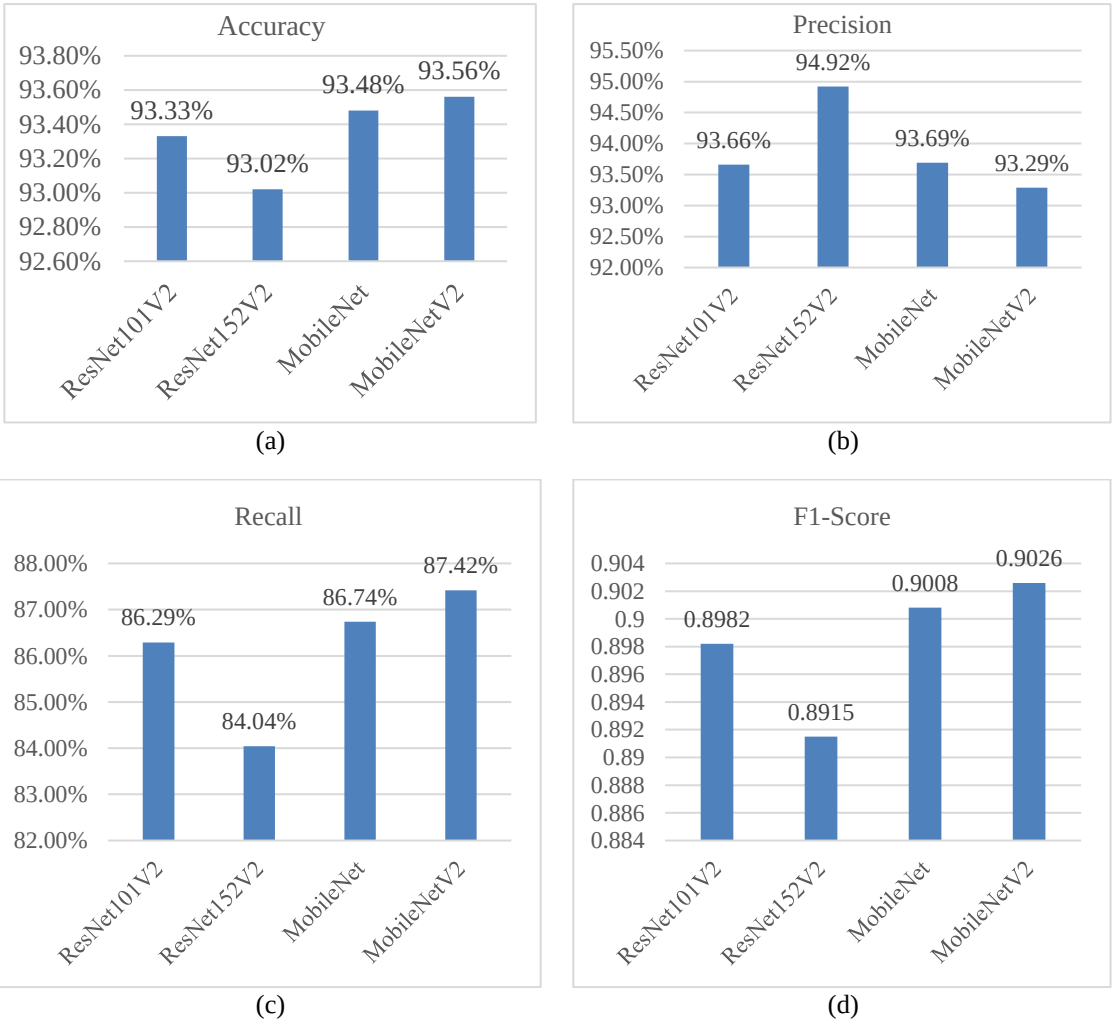

Figure 4. Benchmark of; (a) accuracy, (b) precision, (c) recall, and (d) F1-score

4. CONCLUSION

This study conducted a comparative analysis of four widely used CNN architectures—ResNet101V2, ResNet152V2, MobileNet, and MobileNetV2—based on key performance metrics: accuracy, precision, recall, and F1-score. Among the evaluated models, MobileNetV2 emerged as the top performer, demonstrating superior accuracy and the best balance between precision and recall. Its performance, combined with its lightweight architecture, makes it particularly well-suited for deployment in mobile and edge computing environments where computational resources, memory, and energy efficiency are constrained. This positions MobileNetV2 as a highly practical model for real-world applications such as mobile health diagnostics, on-device image recognition, and intelligent IoT systems.

In summary, the results highlight the necessity of aligning model selection not only with performance requirements but also with deployment constraints, particularly in mobile computing contexts. MobileNetV2, in particular, offers an optimal solution that balances high classification performance with a mobile-friendly design. Future work may focus on optimizing these models further through techniques such as quantization and pruning, as well as validating their effectiveness across diverse mobile applications and hardware configurations. The results demonstrate that mobile-based iris analysis can achieve sensitivity comparable to established screening methods while offering significant advantages in accessibility, cost, and deployment flexibility. The 596 ms inference time enables real-time screening applications suitable for point-of-care use in diverse healthcare settings.

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Tuan Anh Le	✓								✓	✓		✓		
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C : **C**onceptualization
M : **M**ethodology
So : **So**ftware
Va : **Va**lidation
Fo : **Fo**rmal analysis
I : **I**nvestigation
R : **R**esources
D : **D**ata Curation
O : Writing - **O**riginal Draft
E : Writing - Review & **E**diting
Vi : **Vi**sualization
Su : **Su**pervision
P : **P**roject administration
Fu : **Fu**nding acquisition

CONFLICT OF INTEREST STATEMENT

Authors state no conflict of interest.

INFORMED CONSENT

We have obtained informed consent from all individuals included in this study.

DATA AVAILABILITY

The data that support the findings of this study are available from the corresponding author, upon reasonable request.

REFERENCES

[1] H. Sung *et al.*, "Global Cancer Statistics 2020: GLOBOCAN Estimates of Incidence and Mortality Worldwide for 36 Cancers in 185 Countries," *CA: A Cancer Journal for Clinicians*, vol. 71, no. 3, pp. 209–249, 2021, doi: 10.3322/caac.21660.

[2] N. Howlader *et al.*, "SEER Cancer Statistics Review, 1975-2020," *National Cancer Institute*, 2023, [Online]. Available: https://seer.cancer.gov/statfacts/html/lungb.html. (Accessed: June 2, 2025).

[3] B. Lubuzo, T. Ginindza, and K. Hlongwana, "The barriers to initiating lung cancer care in low-and middle-income countries," *Pan African Medical Journal*, vol. 35, no. 1, 2020, doi: 10.11604/pamj.2020.35.38.17333.

[4] U. I. Nwagbara, T. G. Ginindza, and K. W. Hlongwana, "Health systems influence on the pathways of care for lung cancer in low- And middle-income countries: A scoping review," *Globalization and Health*, vol. 16, no. 1, pp. 1–11, 2020, doi: 10.1186/s12992-020-00553-8.

[5] B. Gyawali, G. Bouche, N. Crisp, and N. André, "Challenges and opportunities for cancer clinical trials in low- and middle-income countries," *Nature Cancer*, vol. 1, no. 2, pp. 142–145, 2020, doi: 10.1038/s43018-020-0030-x.

[6] M. Surapaneni and D. Uprety, "Lung cancer management in low and middle-income countries - current challenges and potential solutions," *International Journal of Cancer Care and Delivery*, vol. 3, no. 1, pp. 1–10, 2023, doi: 10.53876/001c.73042.

[7] S. Muzamil, T. Hussain, A. Haider, U. Waraich, U. Ashiq, and E. Ayguadé, "An intelligent iris based chronic kidney identification system," *Symmetry*, vol. 12, no. 12, pp. 1–14, 2020, doi: 10.3390/sym12122066.

[8] C. D. Divya *et al.*, "An efficient machine learning approach to nephrology through iris recognition," *Discover Artificial Intelligence*, vol. 1, no. 1, pp. 1–15, 2021, doi: 10.1007/s44163-021-00010-4.

[9] S. K. Punia, M. Kumar, S. K. Pathak, and X. Cheng, "Diabetes and heart disease identification using biomedical iris data," *Applied and Computational Engineering*, vol. 2, no. 1, pp. 572–581, 2023, doi: 10.54254/2755-2721/2/20220676.

[10] S. Alphonse, R. Venkatesan, and T. J. Jebaseeli, "A Methodical Review of Iridology-Based Computer-Aided Organ Status Assessment Techniques," *Engineering Proceedings*, vol. 59, no. 1, pp. 1–8, 2023, doi: 10.3390/engproc2023059009.

[11] A. Esteva *et al.*, "Dermatologist-level classification of skin cancer with deep neural networks," *Nature*, pp. 115–118, 2017. doi: 10.1038/nature21056.

[12] V. Gulshan *et al.*, "Development and validation of a deep learning algorithm for detection of diabetic retinopathy in retinal fundus photographs," *JAMA - Journal of the American Medical Association*, vol. 316, no. 22, pp. 2402–2410, 2016, doi: 10.1001/jama.2016.17216.

[13] P. Rajpurkar *et al.*, "CheXNet: Radiologist-Level Pneumonia Detection on Chest X-Rays with Deep Learning," *arXiv preprint*, 2017, doi: 10.48550/arXiv.1711.05225.

[14] L. A. Elrefaei, D. H. Hamid, A. A. Bayazed, S. S. Bushnak, and S. Y. Maasher, "Developing Iris Recognition System for Smartphone Security," *Multimedia Tools and Applications*, vol. 77, no. 12, pp. 14579–14603, 2018, doi: 10.1007/s11042-017-5049-3.

[15] A. G. Howard *et al.*, "MobileNets: Efficient Convolutional Neural Networks for Mobile Vision Applications," *arXiv preprint*, 2017, doi: 10.48550/arXiv.1704.04861.

[16] M. Sandler, A. Howard, M. Zhu, A. Zhmoginov, and L. C. Chen, "MobileNetV2: Inverted Residuals and Linear Bottlenecks," in *Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition (CVPR)*, pp. 4510–4520, 2018, doi: 10.1109/CVPR.2018.00474.

[17] P. Rajpurkar, E. Chen, O. Banerjee, and E. J. Topol, "AI in health and medicine," *Nature Medicine*, vol. 28, no. 1, pp. 31–38, 2022, doi: 10.1038/s41591-021-01614-0.

[18] G. C. Forte *et al.*, "Deep Learning Algorithms for Diagnosis of Lung Cancer: A Systematic Review and Meta-Analysis," *Cancers*, vol. 14, no. 16, pp. 1–11, 2022, doi: 10.3390/cancers14163856.

[19] R. Yogeshwaran and S. K. Vishal, "Disease detection based on iris recognition," in *2023 International Conference on Energy, Materials and Communication Engineering (ICEMCE)*. Madurai, India, 2023, pp. 1-5, doi: 10.1109/ICEMCE57940.2023.10433979.

[20] S. M. McKinney *et al.*, "International evaluation of an AI system for breast cancer screening," *Nature*, vol. 577, no. 7788, pp. 89–94, 2020, doi: 10.1038/s41586-019-1799-6.

[21] C. Y. Cheung *et al.*, "A deep learning model for detection of Alzheimer's disease based on retinal photographs: a retrospective, multicentre case-control study," *The Lancet Digital Health*, vol. 4, no. 11, pp. e806–e815, 2022, doi: 10.1016/S2589-7500(22)00169-8.

[22] Banowati, Citra, A. Novianty, and C, Setianingsih, "Cholesterol level detection based on iris recognition using convolutional neural network method," in *2019 IEEE Conference on Sustainable Utilization and Development in Engineering and Technologies (CSUDET)*, Penang, Malaysia, 2019, pp. 116-121, doi: 10.1109/CSUDET47057.2019.9214690.

[23] V. V. Avhad and J. W. Bakal. "An advanced deep learning model for iridology based disease diagnosis using Pyramid network driven iris segmentation," *Biomedical Signal Processing and Control*, vol. 105, p. 107595, 2025, doi: 10.1016/j.bspc.2025.107595.

[24] I. Sonni *et al.*, "Initial experience with a SiPM-based PET/CT scanner: influence of acquisition time on image quality," *EJNMMI Physics*, vol. 5, no. 1, pp. 1-12, 2018, doi: 10.1186/s40658-018-0207-x.

[25] R. Dwivedi *et al*., "Explainable AI (XAI): Core ideas, techniques, and solutions," *ACM Computing Surveys*, vol. 55, no. 9, pp. 1-33, 2023, doi: 10.1145/3561048.

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