Intelligent System for Early Myopia Diagnosis using Deep Learning Approach

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1. Abstract

In recent years, myopia (commonly known as short-sightedness) has become one of the most rapidly increasing vision-related disorders across the globe, particularly among children and young adults. This sharp rise is strongly linked to modern lifestyle patterns, including excessive screen time due to smartphones, laptops, and other digital devices, reduced outdoor activities, and prolonged engagement in near-vision tasks such as reading and gaming. As societies continue to become more technology-driven, the prevalence of myopia is expected to grow even further, making it a significant public health concern in the coming years. Despite being a common condition, myopia can lead to serious complications if not detected and managed at an early stage. High or progressive myopia increases the risk of severe eye disorders such as retinal detachment, glaucoma, cataracts, and myopic macular degeneration, which may ultimately result in irreversible vision loss. Therefore, early diagnosis and timely intervention are essential to control its progression and prevent long-term damage. However, conventional diagnostic approaches typically require specialized ophthalmic equipment and expert medical professionals, which may not always be accessible or affordable, especially in rural and underserved areas. To address these limitations, this study focuses on the development of an intelligent, automated, and efficient deep learning-based system for the early detection of myopia using retinal fundus images. Fundus imaging provides a detailed view of the internal structures of the eye, including the retina, optic disc, and blood vessels, making it a valuable tool for detecting various ocular conditions. By integrating artificial intelligence with medical imaging, the proposed system aims to assist healthcare professionals in making faster, more accurate, and reliable diagnostic decisions.The proposed approach utilizes advanced deep learning architectures, specifically ResNet50 and MaxViT, for image classification. ResNet50, a widely used convolutional neural network, is known for its ability to handle deep architectures efficiently through residual learning, while MaxViT (Multi-Axis Vision Transformer) combines the strengths of convolutional operations and transformer-based attention mechanisms to capture both local and global features effectively. These models are trained and evaluated on a large dataset consisting of more than 20,000 retinal fundus images, which are carefully divided into training, validation, and testing sets to ensure robust performance evaluation and avoid overfitting. Extensive experimental analysis demonstrates that both models perform effectively in detecting myopia; however, the MaxViT model consistently outperforms ResNet50 in terms of classification accuracy, feature extraction capability, and overall reliability. The improved performance of MaxViT can be attributed to its hybrid architecture, which enables better understanding of complex patterns in retinal images. The results highlight the potential of transformer-based models in advancing medical image analysis and improving diagnostic accuracy.

Keywords: ***Myopia, Fundus Image, Classificattion, Deep Learning Models, Vision Transformer***

1. Introduction

Myopia, commonly known as near- sightedness, is a condition in which distant objects appear blurred while nearby objects remain clear. It has become one of the most common vision disorders worldwide. The prevalence of myopia has increased significantly over the past few decades, and it is estimated that nearly half of the global population will be affected by this condition by 2050. The rapid increase in myopia cases is largely associated with modern lifestyle changes, including increased screen time, reduced outdoor activities, and prolonged near work. Genetic factors also contribute to the development of this condition. Traditional methods for diagnosing myopia rely on manual examination by ophthalmologists, which can be time- consuming and dependent on expert availability. In many rural and underdeveloped areas, access to proper eye care services is limited, leading to delayed diagnosis. With the advancement of artificial intelligence, deep learning has emerged as a powerful tool for medical image analysis. By leveraging deep learning models, it is possible to automate the detection process and improve diagnostic efficiency. This research aims to develop an intelligent system that can analyse retinal images and detect myopia at an early stage.

2. Literature Review

Several studies have explored the use of machine learning and deep learning techniques for detecting myopia and other eye- related diseases. Convolutional Neural Networks (CNNs) have been widely used due to their ability to automatically extract relevant features from images. Earlier approaches relied on traditional machine learning algorithms combined with manual feature extraction techniques. While these methods achieved moderate success, they often lacked accuracy and scalability. Recent advancements have introduced more powerful architectures such as ResNet and Vision Transformers. These models are capable of capturing both local and global features, leading to improved classification performance. However, existing systems still face challenges such as limited dataset size, class imbalance, and poor generalization. The proposed system addresses these limitations by using a large dataset and advanced hybrid architecture (MaxViT), which improves both accuracy and stability.

3. Methodology

3.1 Dataset

The dataset used in this study consists of approximately 20,871 retinal fundus images categorized into classes such as normal, diffuse, patchy, and tessellated myopia. The dataset is split into training, validation, and testing sets in a ratio of 70:20:10.

3.2 Data Preprocessing

Preprocessing plays a crucial role in improving model performance. The following steps were applied:

i. Image resizing to a fixed resolution

ii. Normalization of pixel values

iii. Data augmentation techniques such as rotation, flipping, and zooming

These steps help in enhancing the diversity of the dataset and reducing overfitting.

3.3 Models Used

- **ResNet50:** A deep convolutional neural network that uses residual connections to improve learning in deeper networks.
- **MaxViT:** A hybrid architecture combining convolutional layers with transformer-based attetion mechanisms for better feature extraction.

4. Implementation

The proposed system was implemented using Python and modern deep learning frameworks. The entire development process was carried out in a structured manner, ensuring efficient training and evaluation of models.

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4.1 Software Requirements

- Programming Language: Python 3.x
- Framework: TensorFlow / Keras
- Libraries: NumPy, Pandas, Matplotlib, Scikit-learn

4.2 Hardware Requirements

Processor: Intel i5 / i7 or equivalent RAM: Minimum 8GB (16GB recommended) GPU: Optional but recommended for faster training

4.3 Model Training

The models were trained using the prepared dataset with proper validation to avoid overfitting. Transfer learning was applied by using pre-trained weights from ImageNet and fine-tuning the models on the retinal dataset. Hyperparameters such as learning rate, batch size, and number of epochs were carefully selected to achieve optimal performance.

4.4 Evaluation

The trained models were evaluated using test data. Performance metrics such as accuracy, precision, recall, and confusion matrix were used to measure effectiveness.

5. Results and Discussion

The performance of the proposed deep learning models was evaluated using standard classification metrics such as accuracy, precision, and recall. These metrics provide a clear understanding of how effectively the models classify retinal fundus images into different categories of myopia.The experimental results indicate that both models perform well; however, the MaxViT model shows superior performance compared to the ResNet50 model. This improvement is mainly due to the ability of MaxViT to capture both local and global features using transformer- based attention mechanisms.

5.1 Performance Comparison

Model	Accuracy	Precision	Recall
ResNet50	82.86%	84.94%	80.76%
MaxVit	87%	87%	87%

From the above results, it is clearly observed that the MaxViT model achieves higher accuracy and maintains a balanced performance across precision and recall. This indicates that the model not only performs well but also produces consistent and reliable predictions.

5.2 Confusion Matrix Analysis

```
Confusion Matrix
[[392   5 100  72]
 [  0 548   2   2]
 [ 56   7 479  10]
 [ 91   8   5 312]]

Classification Report
              precision    recall  f1-score   support

     diffuse       0.73      0.69      0.71       569
      normal       0.96      0.99      0.98       552
      patchy       0.82      0.87      0.84       552
 tessellated       0.79      0.75      0.77       416

    accuracy                           0.83      2089
   macro avg       0.82      0.82      0.82      2089
weighted avg       0.83      0.83      0.83      2089
```

Fig 6.1: Confusion Matrix of Proposed Model

The confusion matrix provides a detailed representation of the classification results. It shows how many instances were correctly and incorrectly classified by the model.From the confusion matrix, it can be observed that the majority of samples are correctly classified, as indicated by the high values along the diagonal. The number of false positives and false negatives is relatively low, which suggests that the model has strong discriminative capability.This indicates that the proposed system is effective in distinguishing between normal and myopic conditions, making it suitable for practical medical applications.

5.3 Training and Validation Performance

To further analyse the performance of the models, training and validation accuracy and loss graphs were examined for both MaxViT and ResNet50 models.

5.3.1 MaxViT Model Analysis

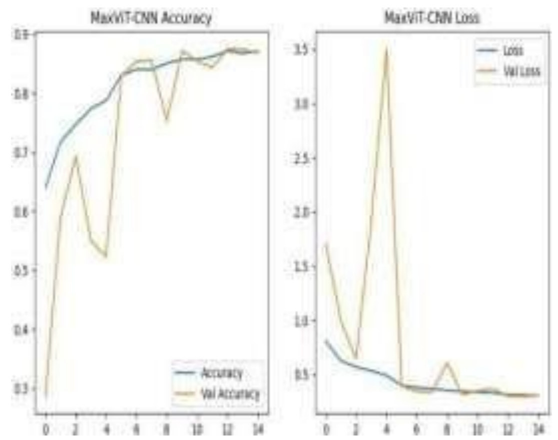

Fig 6.2: Training and Validation Accuracy and Loss of MaxViT Model

The MaxViT model shows a steady increase in training accuracy as the number of epochs increases, indicating effective learning of features from the dataset. The validation accuracy also follows a similar trend, which suggests that the model generalizes well to unseen data.In the initial epochs, slight fluctuations can be observed in validation accuracy. This is a common phenomenon during early training stages, where the model is still adjusting its parameters. However, as training progresses, the model stabilizes and achieves high accuracy.Although minor fluctuations are observed in the initial stages, the model stabilizes over time and achieves a high accuracy of around 87%. This demonstrates that the model is capable of learning complex patterns present in retinal images.The loss curves show a decreasing trend for both training and validation loss. A small spike in validation loss can be observed in the early epochs, which is common during the initial learning phase. However, the loss stabilizes in later stages, indicating proper convergence of the model.Overall, the MaxViT model exhibits stable learning behaviour and strong generalization performance.

5.3.2 ResNet50 Model Analysis

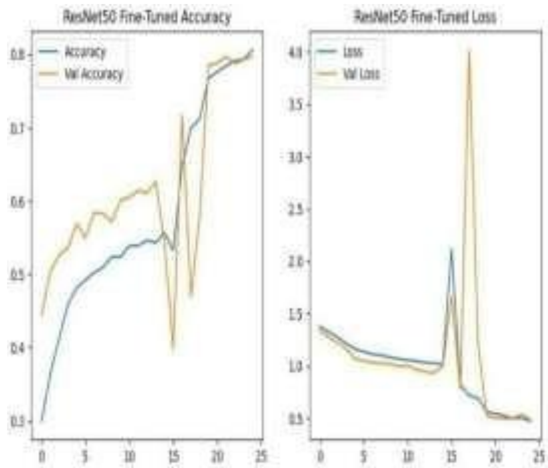

Fig 6.2: Training and Validation Accuracy and Loss of ResNet50 Model

The ResNet50 model also demonstrates an increase in training accuracy over epochs, showing that the model is learning from the dataset. However, compared to MaxViT, the improvement is relatively slower and less consistent.The validation accuracy shows noticeable fluctuations, especially in the middle epochs, indicating some instability during training. This may be due to limitations in capturing complex image features. The loss graph shows an overall decreasing trend, but with occasional spikes in validation loss. These spikes suggest that the model may experience slight overfitting or difficulty in generalizing across all classes.Despite these variations, the model achieves a reasonable accuracy of around 82–83%, making it a reliable but slightly less efficient model compared to MaxViT.

5.4 Comparative Discussion

A detailed comparison between the two models highlights the strengths of the MaxViT architecture. The ability to integrate convolutional operations with **attention** mechanisms allows MaxViT to capture more complex relationships within the data.In contrast, ResNet50 primarily relies on convolutional feature extraction, which may limit its ability to capture global context. This difference becomes evident in the performance metrics and training behavior of the models. Another important observation is the stability of the learning process. The MaxViT model shows smoother training and validation curves, indicating better convergence and generalization. From a practical perspective, the improved performance of MaxViT makes it more suitable for deployment in real-world healthcare systems, where accuracy and reliability are critical.

5.5 Comparison with Existing Methods

To further evaluate the effectiveness of the proposed system, a comparison was made with traditional and existing approaches used for myopia detection. The comparison is based on key factors such as accuracy, processing speed, accessibility, and ability to handle real-time data.

5.6 Comparison Analysis

The comparison between Traditional Methods, Existing Machine Learning Models, and the Proposed System based on MaxViT clearly illustrates the technological advancements in medical image analysis, particularly in ECG classification. Traditional methods primarily depend on manual interpretation by medical experts. While these approaches have been widely used for decades, they are inherently limited by human factors such as fatigue, variability in expertise, and time constraints. As a result, they offer only moderate accuracy and are generally slow in processing. Additionally, these methods lack automation and real-time capabilities, making them unsuitable for large- scale or time-sensitive healthcare applications. Existing Machine Learning (ML) models represent a significant improvement over traditional approaches. Techniques such as Convolutional Neural Networks (CNNs) and other deep learning architectures enable automated feature extraction and classification, resulting in higher accuracy compared to manual methods. These models also introduce a degree of automation, reducing human effort. However, many existing ML models still face challenges such as moderate processing speed, limited real- time performance, and restricted generalization when applied **to** diverse or unseen datasets. This limits their effectiveness in dynamic clinical environments. In terms of performance, the proposed system offers faster processing speed due to optimized architecture and efficient computation. It is fully automated, eliminating the need for manual intervention and significantly reducing the chances of human error. One of the key advantages of the system is its real-time capability, allowing instant analysis and decision- making, which is critical in emergency healthcare scenarios

6. Future Scope

Although the proposed system demonstrates promising results, there are several areas for future improvement.One possible direction is the integration of the system into mobile or web-based applications, which would allow users to access diagnostic tools remotely. This would be particularly beneficial in rural areas where access to healthcare services is limited.Another important improvement is the use of larger and more diverse datasets. This would help in improving the robustness and generalization of the model across different populations.The system can also be enhanced by incorporating real-time processing capabilities, enabling instant diagnosis. Additionally, integration with cloud platforms can allow for scalable deployment and centralized data management. Future research may also explore the use of other advanced architectures and ensemble models to further improve accuracy and reliability.

7. Conclusion

This study presents a deep learning-based approach for early detection of myopia using retinal fundus images. The results demonstrate that advanced architectures such as MaxViT significantly improve classification performance compared to traditional convolutional models. The system is capable of achieving high accuracy while maintaining stability and generalization. This makes it suitable for large- scale screening and real- world deployment. One of the key contributions of this work is the use of a hybrid model that combines the strengths of convolutional and transformer- based architectures. This approach enables the system to capture complex patterns in medical images more effectively. Overall, the proposed system has the potential to assist healthcare professionals in early diagnosis, reduce workload, and improve patient outcomes.

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