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Eye Disease Classification Using VGG-19 and TensorFlow on Fundus Images

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Abstract Eye disorders are health problems that can reduce visual quality and may lead to blindness if they are not detected at an early stage. The use of deep learning technology has become a promising approach to support the classification of eye diseases based on medical images. This study aims to classify eye diseases from fundus images using a Convolutional Neural Network architecture based on VGG-19 with the support of TensorFlow and Keras frameworks. The dataset used in this study was obtained from Kaggle and consists of eight classes, namely Normal, Cataract, Diabetes, Glaucoma, Hypertension, Myopia, Age Issues, and Other. The research stages include data collection, image preprocessing, dataset generation, training and testing data splitting, VGG-19 model design using transfer learning, model training, model testing, and evaluation using accuracy, precision, recall, F1-score, and confusion matrix. The testing results show that the model achieved an accuracy of 78.24% on the testing data with a loss value of 0.0983. Meanwhile, evaluation using k-fold cross validation obtained an accuracy of 91.35% with a margin of ±2.25%. The confusion matrix results indicate that Cataract and Myopia achieved the best classification performance, while the Normal class still showed a low recall value. These findings indicate that TensorFlow-based VGG-19 can be used for eye disease classification, although further development is still needed to improve the model's generalization ability.

Keywords *Customer Churn; E-Commerce; Machine Learning; Tree-Based Gradient Boosted Models; XGBoost*

1. INTRODUCTION

The eye is a sensory organ that plays an important role in human vision. Eye disorders can directly affect a person's quality of life, productivity, and independence. Blindness is one of the most concerning health issues because it can occur due to delays in the detection and treatment of eye diseases. Based on the Rapid Assessment of Avoidable Blindness conducted by the Indonesian Ministry of Health from 2014 to 2016, 3% of the population aged over 50 years experienced blindness (Muhlashin & Stefanie, 2023). In addition, the number of individuals experiencing visual impairment globally is estimated to increase from 1.1 billion in 2020 to 1.76 billion by 2050 (Indraswari et al., 2022). This condition highlights the importance of early detection of eye diseases to reduce the risk of severe visual impairment. One of the eye disorders that commonly causes blindness is cataract. Cataracts can be influenced by various factors, such as aging, history of eye disease, drug toxicity, metabolic disorders, genetic abnormalities, ultraviolet exposure, and smoking habits. Other eye diseases, such as glaucoma, diabetic retinopathy, myopia, hypertension-related eye disorders, and age-related eye disorders, can also reduce visual quality if they are not treated early. In medical practice, fundus images are often used to detect various eye disorders because they visually represent the condition of the retina and eye structures (Indraswari et al., 2022). Therefore, fundus image analysis plays an important role in the development of technology-based eye disease classification systems.

The development of artificial intelligence, particularly deep learning, provides significant opportunities in medical image processing. Deep learning is a part of machine learning that uses multilayer artificial neural networks to automatically learn patterns from data (Hasma & Silfianti, 2018). One deep learning method widely used in image classification is the Convolutional Neural Network (CNN). CNN can extract visual features from images through convolutional layers, pooling layers, and fully connected layers, making it effective for image classification, object detection, and image segmentation tasks (Dewi & Ismawan, 2021; Ibrahim et al., 2022). In the context of eye disease classification, CNN can help identify specific visual patterns that may be difficult for the general public to distinguish directly.

Several previous studies have applied deep learning methods for eye disease classification. Marcella et al. (2022) used CNN with the VGG-19 architecture to classify eye diseases and obtained the best accuracy of 65.29%. Another study by Muhlashin and Stefanie (2023) applied YOLOv8 to fundus images for eye disease classification and achieved an accuracy of 92%, precision of 91%, recall of 92%, and F1-score of 91%. In addition, an expert system based on Bayes' theorem has also been used to diagnose eye diseases, particularly refractive disorders, as a web-based consultation tool (Qamaruzzaman & Ani, 2016). These studies show that technology-based approaches can support the detection and classification of eye disorders.

However, research on eye disease classification using fundus images still has room for further development, particularly in the use of transfer learning-based CNN architecture with the TensorFlow framework. VGG-19 is one of the popular CNN architectures because it has a deep network structure and has been trained on the ImageNet dataset, allowing it to be used as a base model for medical image classification (Haksoro & Setiawan, 2021; Marcella et al., 2022). By utilizing transfer learning, the model can use initial weights learned from a large-scale dataset and then be adapted to the fundus image dataset for eye disease classification.

Based on these problems, this study aims to classify eye diseases using the VGG-19 architecture based on Convolutional Neural Network with the support of TensorFlow and Keras. This study focuses on eight diagnosis classes, namely Normal, Cataract, Diabetes, Glaucoma, Hypertension, Myopia, Age Issues, and Other. The model evaluation was conducted using accuracy, precision, recall, F1-score, and confusion matrix to determine the model's ability to recognize each eye disease class.

2. RESEARCH METHODS

2.1. Research Design

This study uses an experimental method with a deep learning approach to classify eye diseases based on fundus images. The model used is a Convolutional Neural Network based on the VGG-19 architecture with the application of transfer learning. The research was conducted through several stages, namely problem identification, literature review, data collection, data preprocessing, model design, model implementation, model training, model testing, and result evaluation.

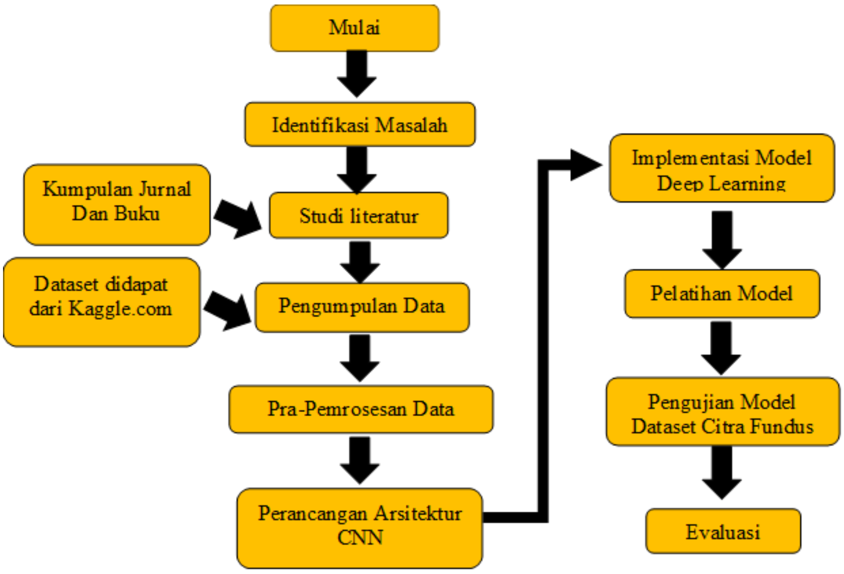

Figure 1. Research Method Framework

The problem identification stage was carried out to understand the need for early detection of eye diseases based on fundus images. The literature review stage was conducted by examining scientific articles related to deep learning, CNN, VGG-19, TensorFlow, Keras, and eye disease classification. The data collection stage was carried out by obtaining a public dataset from Kaggle. After that, the data were processed to make them ready for model training and testing.

2.2. Tree-Based Gradient Boosted Models

The dataset used in this study is an eye fundus image dataset obtained from Kaggle. The dataset contains metadata in CSV format and fundus images that have gone through preprocessing stages. The data were used to classify eight eye conditions, namely Normal, Cataract, Diabetes, Glaucoma, Hypertension, Myopia, Age Issues, and Other. After the dataset generation process was completed, the fundus images were grouped into several diagnosis classes. The number of data in each class is shown in Table 1.

Table 1. Model Evaluation Results

No	Class	Number of Data
1	Normal	700
2	Cataract	594
3	Diabetes	1818
4	Glaucoma	610

5	Hypertension	374
6	Myopia	479
7	Age Issues	551
8	Other	324

The image dataset was then processed into a uniform size of 224 × 224 pixels with three RGB color channels. This size was adjusted to the input requirements of the VGG-19 architecture. The data were then divided into training data and testing data using an 80:20 ratio.

Figure 2. Dataset

2.3. Data Preprocessing

Data preprocessing was conducted to ensure that the fundus images were in an appropriate format before being used in the model training process. This stage included image reading, color conversion from BGR to RGB, image resizing to 224 × 224 pixels, class labeling, data shuffling, and label conversion into one-hot encoding format. The preprocessing process was carried out using several Python libraries, such as OpenCV, NumPy, Pandas, TensorFlow, and Keras. Python was selected because it has relatively simple syntax and is widely used in the development of machine learning and deep learning models (Syahrudin & Kurniawan, 2018). TensorFlow was used as the main framework for building the deep learning model, while Keras was used to simplify the construction of the neural network architecture (Hasma & Silfianti, 2018; Jakaria et al., 2021). One-hot encoding was used to convert categorical labels into numerical representations in the form of binary vectors. This process is important because deep learning models require numerical label inputs to perform learning in multi-class classification problems.

2.4. VGG-19 Model Design

The model used in this study is VGG-19 based on transfer learning. VGG-19 is a CNN architecture consisting of 19 layers, including 16 convolutional layers and 3 fully connected layers. This architecture is widely used in image classification tasks because it can extract deep visual features through small convolutional filters (Marcella et al., 2022). In this study, the VGG-19 model was loaded with initial ImageNet weights, and the top layer was removed. The VGG-19 layers were used as feature extractors with frozen parameters, meaning that the weights in the base layers were not updated during the training process. Several layers were added on top of the VGG-19 model, namely Flatten, Dense with 256 neurons and ReLU activation, Batch Normalization, a second Dense layer with 256 neurons, a second Batch Normalization layer, and an output Dense layer with 8 neurons and softmax activation.

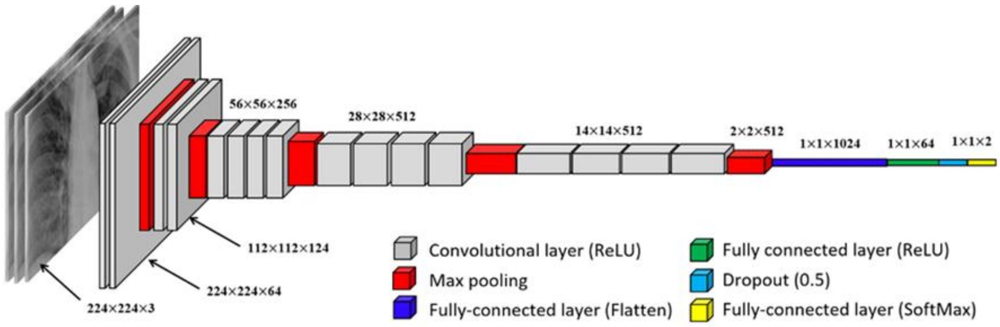

Figure 3. VGG-19 Model Architecture

The developed model has a total of 26,517,064 parameters. Of this number, 6,491,656 parameters are trainable, while 20,025,408 parameters are non-trainable because they come from the pre-trained VGG-19 model. This structure allows the model to utilize the feature extraction capability of VGG-19 while adjusting the final classification layers to the eight eye disease classes.

2.5. Model Training

The model was trained using the Adam optimizer, categorical crossentropy loss function, and accuracy metric. The Adam optimizer was used because it is effective in updating model weights during training. The categorical crossentropy loss function was used because this study deals with a multi-class classification problem. The model was trained using a batch size of 32 and 15 epochs. During the training process, fundus images in the training data were entered into the model in batches. Each batch passed through the VGG-19 layers and the additional layers that had been designed. The model then generated predictions that were compared with the actual labels. The difference between the predictions and the actual labels was calculated as the loss value, and the trainable parameters were then updated through the backpropagation process.

2.6. Model Testing and Evaluation

Model testing was conducted using testing data that were not used during the training process. The model predicted the class of each fundus image, and the prediction results were compared with the actual labels. The testing results were visualized in a grid format displaying the image, actual label, and predicted label. The model was evaluated using several metrics, namely accuracy, precision, recall, F1-score, and confusion matrix. These metrics were used to assess overall model performance as well as the model's ability to recognize each class. The evaluation formulas used are as follows:

$$\text{Accuracy} = (TP + TN) / \text{Total Data}$$

$$\text{Precision} = TP / (TP + FP)$$

$$\text{Recall} = TP / (TP + FN)$$

$$\text{F1-score} = 2 \times (\text{Precision} \times \text{Recall}) / (\text{Precision} + \text{Recall})$$

Precision is used to measure the correctness of positive predictions, recall is used to measure the model's ability to identify actual positive data, while F1-score is used to balance precision and recall.

3. RESULTS

3.1. Data Preprocessing Results

The initial stage of the study was conducted by reading data from the CSV file using the Pandas library. The data contained information about eye fundus images, gender, age, eye diagnosis, and diagnostic labels. After the data were successfully read, the right and left eye images were separated so that each image could be processed independently. This process aimed to simplify the creation of a fundus image dataset that was ready to be used in deep learning model training. In the preprocessing stage, all images were resized to 224 × 224 pixels and converted into RGB format. The dataset was then shuffled to avoid overly structured data sequences. After that, class labels were converted into one-hot encoding format so that they could be processed by the multi-class classification model.

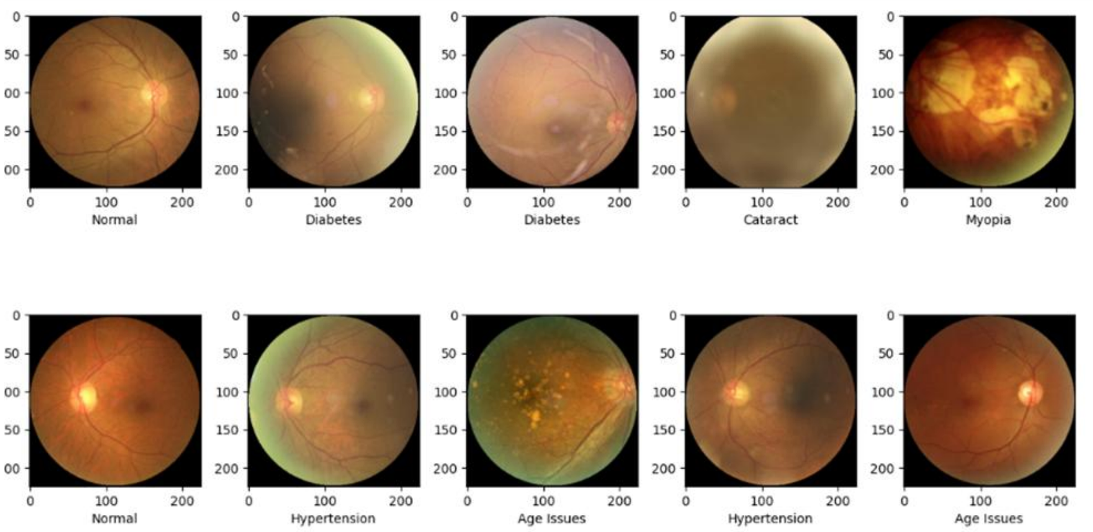

Figure 4. Random Samples of the Fundus Image Dataset

Visualisasi sampel acak dataset menunjukkan bahwa setiap citra telah memiliki label diagnosis, seperti Normal, Cataract, Diabetes, Glaucoma, Hypertension, Myopia, Age Issues, dan Other. Visualisasi ini penting untuk memastikan bahwa citra yang digunakan sesuai dengan label kelasnya sebelum model dilatih.

3.2. Model Design Results

The developed model used VGG-19 as the base model. The VGG-19 layers generated an output with a size of 7 × 7 × 512, which was then flattened using the Flatten layer into a one-dimensional vector. After that, the feature vector was processed through two Dense layers, each with 256 neurons and ReLU activation. Batch Normalization layers were added after each Dense layer to help stabilize the training process. The output layer used softmax activation with 8 neurons according to the number of diagnostic classes.

Layer (type)	Output Shape	Param #
vgg19 (Functional)	(1, 7, 7, 512)	20,024,384
flatten (Flatten)	(1, 25088)	0
dense (Dense)	(1, 256)	6,422,784
batch_normalization (BatchNormalization)	(1, 256)	1,024
dense_1 (Dense)	(1, 256)	65,792
batch_normalization_1 (BatchNormalization)	(1, 256)	1,024
dense_2 (Dense)	(1, 8)	2,056

Total params: 26,517,064 (101.15 MB)
Trainable params: 6,491,656 (24.76 MB)
Non-trainable params: 20,025,408 (76.39 MB)

Figure 5. VGG-19 Model Summary

The model summary shows that the model has a total of 26,517,064 parameters. The non-trainable parameters came from the VGG-19 model trained on ImageNet, while the trainable parameters came from the additional layers used to adapt the model for eye disease classification. The use of transfer learning is expected to reduce training time and improve the model's ability to extract features from fundus images.

3.3. Model Training Results

The model was trained using training data with a batch size of 32 and 15 epochs. The training results show that the model was able to learn patterns from the fundus images used. After the training process was completed, the model was tested using testing data to determine its performance on unseen data.

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Accuracy: 91.35% (+/- 2.25%)
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Figure 6. Deep Learning Model Training Results

Hasil pengujian pada data testing menunjukkan bahwa model memperoleh accuracy sebesar 78,24% dengan nilai loss sebesar 0,0983. Nilai accuracy tersebut menunjukkan bahwa model mampu mengklasifikasikan sebagian besar citra fundus dengan benar, meskipun masih terdapat beberapa kesalahan klasifikasi pada kelas tertentu. Sementara itu, nilai loss yang rendah menunjukkan bahwa model mampu mempelajari pola data dengan cukup baik. Selain pengujian menggunakan data testing, evaluasi juga dilakukan menggunakan k-fold cross validation. Hasil evaluasi menunjukkan bahwa model VGG-19 memperoleh akurasi sebesar 91,35% dengan margin ±2,25%. Hal ini menunjukkan bahwa model memiliki potensi yang baik dalam melakukan klasifikasi kelainan mata, meskipun performa pada data testing tetap perlu diperhatikan sebagai indikator kemampuan generalisasi model.

3.4. Confusion Matrix Results

The confusion matrix was used to identify the distribution of correct and incorrect predictions in each class. The confusion matrix results are shown in Table 2.

Table 2. Confusion Matrix of Eye Disease Classification

Actual / Predicted	**Normal**	**Cataract**	**Diabetes**	**Glaucoma**	**Hypertension**	**Myopia**	**Age Issues**	**Other**
Normal	47	3	49	20	1	2	9	6
Cataract	0	119	2	2	0	0	0	0
Diabetes	7	0	300	19	8	4	6	5
Glaucoma	0	2	7	94	0	0	3	1
Hypertension	1	0	16	8	42	0	7	0
Myopia	0	0	0	1	0	100	2	0
Age Issues	4	0	14	6	1	2	97	0
Other	2	0	7	4	0	0	2	46

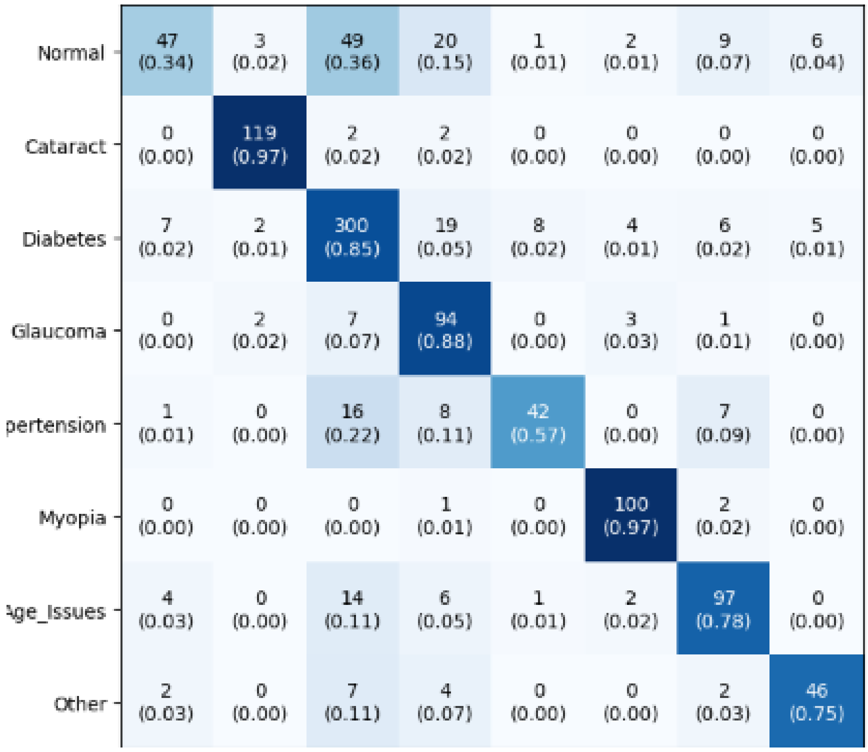

Figure 7. Confusion Matriks

Based on the confusion matrix, the model showed very good performance in the Cataract and Myopia classes. In the Cataract class, the model correctly classified 119 data samples. In the Myopia class, the model correctly classified 100 data samples. However, in the Normal class, the model still experienced difficulty because many Normal data samples were predicted as other classes, especially Diabetes and Glaucoma. This indicates that the visual characteristics of the Normal class are still difficult for the model to distinguish from several eye disease classes.

3.5. Precision, Recall, and F1-Score Results

Based on the confusion matrix, the precision, recall, and F1-score values for each class were recalculated to ensure consistency with the prediction data. The evaluation results are shown in Table 3.

Table 3. Precision, Recall, and F1-Score Results

Class	Precision	Recall	F1-Score
Normal	0.770	0.343	0.475
Cataract	0.960	0.967	0.964
Diabetes	0.759	0.860	0.806
Glaucoma	0.610	0.879	0.720
Hypertension	0.808	0.568	0.667
Myopia	0.926	0.971	0.948
Age Issues	0.770	0.782	0.776
Other	0.793	0.754	0.773
Macro Average	**0.800**	**0.765**	**0.766**

The evaluation results show that the Cataract and Myopia classes achieved the best performance. The Cataract class obtained precision of 0.960, recall of 0.967, and F1-score of 0.964. The Myopia class obtained precision of 0.926, recall of 0.971, and F1-score of 0.948. These results indicate that the model was able to recognize both classes very well. In the Diabetes class, the model obtained precision of 0.759, recall of 0.860, and F1-score of 0.806. These values indicate that the model performed reasonably well in recognizing fundus images with Diabetes diagnosis. Meanwhile, the Glaucoma class obtained a high recall value of 0.879, but its precision was still low at 0.610. This indicates that the model was able to detect many Glaucoma cases, but it still produced a considerable number of incorrect predictions for this class. The Normal class had the lowest recall value, at 0.343. This indicates that many Normal fundus images were not successfully recognized as Normal. This condition may be caused by similarities in visual characteristics between Normal images and several eye disease classes, variations in image quality, or class distribution imbalance. Therefore, improvements in preprocessing quality, data augmentation, and model adjustment are still needed to improve the performance of the Normal class. Overall, the evaluation results show that the TensorFlow-based VGG-19 model has reasonably good capability in classifying eye diseases based on fundus images. However, the model performance is not yet evenly distributed across all classes. Some classes with clearer visual patterns, such as Cataract and Myopia, can be classified well, while Normal and Hypertension still require further model improvement to increase recall values.

4. CONCLUSIONS

Based on the results of this study, it can be concluded that the deep learning model based on the VGG-19 architecture with TensorFlow and Keras can be used to classify eye diseases based on fundus images. This model is able to classify eight diagnostic classes, namely Normal, Cataract, Diabetes, Glaucoma, Hypertension, Myopia, Age Issues, and Other. The use of transfer learning through initial ImageNet weights helps the model extract visual features from fundus images, making the training process more efficient. The testing results show that the model achieved an accuracy of 78.24% on testing data with a loss value of 0.0983. In addition, evaluation using k-fold cross validation produced an accuracy of 91.35% with a margin of ±2.25%. Based on the confusion matrix, Cataract and Myopia showed the best performance, with F1-scores of 0.964 and 0.948, respectively. Meanwhile, the Normal class had a low recall value of 0.343, indicating that the model still experienced difficulty distinguishing normal eye images from several eye disease classes. Practically, this model has the potential to support early detection of eye diseases based on fundus images. However, the model still needs further development, particularly through increasing the amount of data, improving image quality, applying data augmentation, balancing class distribution, and exploring other architectures such as EfficientNet, ResNet, or Vision Transformer. Future studies are also recommended to validate the model using more diverse datasets so that the model can achieve better generalization ability in supporting medical image classification applications.

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