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Investigation of the efficiency of neural network models for developing a classifier of ophthalmic pathologies

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ABSTRACT

This study presents the development and evaluation of a machine learning-based system for the classification of ophthalmic diseases using fundus images. The dataset consists of images categorized into four main classes: cataract, diabetic retinopathy, glaucoma, and healthy eye. To ensure the accuracy and reliability of the models, the data underwent preprocessing steps, including outlier detection, normalization, balancing, and splitting into training and testing sets. Three deep learning models - VGG16, VGG19, and EfficientNet were utilized for disease classification. The experimental results demonstrated high prediction accuracy across different disease categories, with EfficientNet achieving the highest performance (up to 96.94% for diabetic retinopathy). The system allows users to upload eye images, select a model, and obtain diagnostic predictions with specified accuracy levels. The models were rigorously tested using the Python unittest framework, confirming their stability and reliability. The findings highlight the potential of machine learning in improving ophthalmic disease diagnosis, reducing diagnostic time, and enhancing medical decision-making. The integration of these models into medical practice can significantly improve the quality of healthcare services and assist doctors in providing more efficient and accurate diagnoses.

Keywords: Machine learning; ophthalmic disease classification; fundus images; deep learning; VGG16; VGG19; EfficientNet; medical image analysis

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INTRODUCTION

In today's world, ophthalmic pathologies are one of the main causes of vision loss, which significantly affects the quality of life of patients. Eye diseases, such as cataracts, glaucoma, diabetic retinopathy, and macular degeneration, are common among different age groups, which necessitate timely diagnosis and effective treatment. Traditional diagnostic methods require considerable effort and time for a qualified assessment of the patient's condition, which often limits the availability of medical services and complicates the timely detection of pathologies.

In this regard, automation of diagnostic processes using modern technologies, including artificial intelligence (AI) methods, is becoming increasingly important.

One of the most promising areas of AI application in medicine is the use of neural networks for medical image classification. Convolutional neural networks (CNNs) are one of the most effective tools for automatic image processing, as they not only automatically detect important features in images, but also provide high accuracy and efficiency in solving computer vision tasks [1].

The relevance of building a classifier of ophthalmic pathologies using CNNs lies in the ability of such systems to reduce the workload of medical professionals, speed up the diagnostic process, and increase the accuracy of detecting diseases at early stages, which, in turn, contributes to more effective treatment and prevention of vision loss. In particular, the development and implementation of automatic classifiers of ophthalmic pathologies has significant potential to improve medical practice, reduce the cost of medical image processing, and improve the quality of life of patients [2, 3].

ANALYSIS OF LITERATURE DATA

In recent years, the application of artificial intelligence (AI) and deep learning methods in the field of ophthalmology has gained significant attention, primarily due to their potential to enhance diagnostic accuracy, reduce the time required for image analysis, an assist medical professionals in detecting ophthalmic pathologies at an early stage [4, 5], [6, 7], [8]. Various studies have explored different deep learning models, especially Convolutional Neural Networks (CNNs), for the classification and detection of ophthalmic diseases such as diabetic retinopathy, glaucoma, age-related macular degeneration, and cataracts.

In particular, the use of machine learning in automating image analysis is a promising area, as it allows computer systems to learn from large amounts of data and identify hidden patterns that may be difficult for the human eye to see [9, 10], [11, 12]. Modern deep learning methods provide high accuracy in image classification and can significantly improve the diagnostic process. Choosing the right models and algorithms is critical to achieving reliable and accurate results [13]

Convolutional Neural Networks (CNNs) have become the go-to method for image classification tasks, owing to their ability to learn hierarchical features directly from raw image data without manual intervention [14, 15], [16]. Let's describe below several studies that investigated CNN architectures for the classification of ophthalmic diseases.

1. LeNet-5 and AlexNet CNN models were among the first to demonstrate the potential of deep learning for image classification tasks. However, their relatively simple architectures limited their ability to handle complex ophthalmic images.

2. The VGG-16 and VGG-19 architectures, introduced by the Visual Geometry Group at Oxford, have become widely used in the field of medical image analysis due to their simple yet effective design. These models, with deep layers of convolutional filters, have shown promising results in detecting diseases like diabetic retinopathy and cataracts.

3. ResNet50, ResNet101, and other variants of ResNet introduced the concept of residual learning, which allows for the training of very deep networks by addressing the vanishing gradient problem. This architecture has been applied successfully to various ophthalmic disease detection tasks, particularly for retinal image analysis.

4. InceptionV3 architecture, developed by Google, uses a more complex structure with inception modules that allow the network to learn multiscale features. It has been employed in the classification of retinal images and has achieved high performance due to its efficient use of resources and ability to handle diverse features.

5. Xception, an extension of Inception, uses depthwise separable convolutions, significantly reducing the number of parameters while maintaining accuracy. It has been applied to ophthalmic pathology classification with promising results, particularly for multi-class classification tasks.

6. MobileNet architecture is designed to be lightweight and efficient, making it suitable for resource-constrained devices. Despite its smaller size, MobileNet has shown competitive results in ophthalmic disease classification and has been used for real-time diagnostic applications.

7. DenseNet connects each layer to every other layer in a feed-forward fashion, which promotes feature reuse and reduces the number of parameters. DenseNet has been applied to retinal image classification and has outperformed traditional models in some studies.

8. EfficientNet, known for its scaling of model depth, width, and resolution in a balanced manner, has been shown to achieve state-of-the-art performance with fewer parameters compared to other architectures. Its use in ophthalmic image classification is growing, with promising results in detecting diabetic retinopathy and other conditions.

In comparing different CNN architectures, several factors must be taken into account: model complexity, parameters, performance.

An analysis of the literature shows that the use of AI technologies in the diagnosis of ophthalmic diseases is being actively researched, and many authors emphasise the advantages of deep neural networks, such as VGG, ResNet, and EfficientNet, in image classification [17, 18], [19, 20]. Studies confirm that AI can contribute not only to the accuracy but also to the speed of the diagnostic process, allowing specialists to pay more attention to assessing the patient's clinical picture [21, 22]. At the same time, the literature indicates that one of the challenges is the need to validate models for clinical use and take into account variations in images that may be caused by various factors, such as the quality of equipment or individual patient characteristics [23].

Thus, automating the diagnosis of ophthalmic diseases using AI can significantly improve the quality of medical services by ensuring timely detection of pathologies and preventing their progression. The use of AI is becoming an important component of modern ophthalmology, allowing to increase the accuracy and efficiency of diagnostic solutions [24, 25].

Ophthalmic pathologies are among the most prevalent medical conditions leading to severe consequences for patients, including vision loss. Many of these diseases, such as diabetic retinopathy, cataracts, glaucoma, and macular degeneration, tend to progress at early stages, making early detection and treatment crucial. However, existing diagnostic methods do not always provide the necessary accuracy or speed, which can result in delays in making the correct diagnosis and initiating treatment [25].

Traditional diagnostic methods, such as ophthalmoscopy, fundus examination, or optical coherence tomography (OCT), while effective, require significant time, human resources, and a high level of expertise from medical practitioners. These methods also struggle to process large volumes of data quickly, which creates a need for the automation of this process [26].

Given these limitations, the application of machine learning and artificial intelligence (AI) technologies [27, 28], [29] for the automated processing of medical images and the detection of pathologies is becoming increasingly relevant.

However, several challenges still exist within this field that need to be addressed such as:

1) low accuracy of existing classifiers;

2) inability to process complex images effectively;

3) limitations of traditional machine learning models;

4) optimization and comparison of different models.

THE PURPOSE AND OBJECTIVES OF THE RESEARCH

The primary purpose of this research is to develop and evaluate an effective deep learning-based classifier for detecting ophthalmic pathologies using Convolutional Neural Networks (CNNs). Specifically, the research aims to compare the performance of various CNN architectures, such as VGG-16, VGG-19, ResNet50, InceptionV3, Xception, MobileNet, DenseNet, and EfficientNet, in terms of their accuracy, computational efficiency, and applicability to real-world ophthalmic diagnostic scenarios. The goal is to identify the most suitable model for early detection and classification of ophthalmic diseases from medical images, such as diabetic retinopathy, glaucoma, cataracts, and macular degeneration.

To achieve this purpose, the following objectives have been formulated.

1. To conduct a comprehensive analysis of existing CNN architectures and their applications in medical image classification, particularly in ophthalmology.

2. To develop a methodology for preprocessing and augmenting ophthalmic image datasets to enhance model training and performance.

3. To implement and train multiple CNN models using standardized datasets of ophthalmic images, ensuring fair comparison across architectures.

4. To evaluate and compare the performance of different CNN architectures based on established metrics including accuracy, precision, recall, F1-score, and computational efficiency.

5. To assess the generalizability of the best-performing models on diverse test datasets that reflect the variability encountered in clinical practice.

6. To propose an optimal CNN-based solution for implementation in clinical ophthalmology practice that balances diagnostic accuracy with computational requirements.

MATERIALS AND RESEARCH METHODS

A number of modern technologies and methods were used to analyse and develop a system for classifying ophthalmic diseases. The main data sources were medical fundus images obtained from open databases. To prepare these images, pre-processing methods, including normalisation, scaling and augmentation, were used to improve data quality.

The main machine learning models used were convolutional neural networks (CNNs), in particular the VGG-16, VGG-19 and EfficientNet architectures. The process of training and testing the models was carried out using TensorFlow and Keras libraries. The data were divided into training and test sets to ensure high-quality model training and verification of their accuracy.

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These models were chosen because of their high accuracy, stability, and efficiency in training on large datasets.

Let`s describe the main arguments in favour of each model selection.

1. EfficientNet provides high performance in classification accuracy at reduced computing costs, which makes it optimal for large datasets. Balance – between performance and efficiency, allowing you to achieve high results even with limited resources. After training for 30 and 50 epochs, the model demonstrated stable high results, which proves its reliability.

2. VGG-19. Due to additional layers compared to VGG-16, VGG-19 achieves better results in classifying complex images. The model has shown high classification accuracy after training for 30 and 50 epochs, making it suitable for medical research applications. VGG-19 maintains stable results at different stages of training, which allows avoiding retraining using the callback function.

3. VGG-16 this model has a simple and efficient architecture that ensures high classification accuracy with minimal computational costs. After 30 and 50 training epochs, the model demonstrates high accuracy in medical image classification tasks. Stability. VGG-16 maintains the stability of results at different stages of training, making it suitable for production systems.

At the initial stage of training (10 epochs), all models showed low classification accuracy (Table 1 Table 2 and Table 3), which indicates insufficient training and the need for further training to more accurately recognise patterns in images.

– EfficientNet: precision - 0.37 recall - 0.38, f1-score - 0.38.

– VGG-19: precision - 0.38, recall - 0.38, f1-score - 0.38.

– VGG-16: precision - 0.39, recall - 0.40, f1-score - 0.39.

Table 1. **EfficientNet model results after training (10 epochs)**

Категорія	precision	recall	f1-score
Normal	0.35	0.36	0.35
Glaucoma	0.40	0.41	0.41
Cataract	0.38	0.37	0.37
Diabetic retinopathy	0.36	0.38	0.37

Source: **compiled by the authors**

Table 2. **VGG-19 model results after training (10 epochs)**

Категорія	precision	recall	f1-score
Normal	0.36	0.37	0.36
Glaucoma	0.41	0.42	0.42
Cataract	0.39	0.38	0.38
Diabetic retinopathy	0.37	0.39	0.38

Source: **compiled by the authors**

Table 3. **VGG-16 model results after training (10 epochs)**

Категорія	precision	recall	f1-score
Normal	0.37	0.38	0.37
Glaucoma	0.42	0.43	0.43
Cataract	0.40	0.39	0.39
Diabetic retinopathy	0.38	0.40	0.39

Source: **compiled by the authors**

Increasing the number of epochs to 30 led to a significant improvement in model performance, all three models demonstrated high performance (Table 4, Table 5 and Table 6).

Table 4. **EfficientNet model results after training (30 epochs)**

Категорія	precision	recall	f1-score
Normal	0.95	0.92	0.93
Glaucoma	0.91	0.91	0.91
Cataract	0.94	0.97	0.95
Diabetic retinopathy	1.0	1.0	1.0

Source: **compiled by the authors**

Table 5. **VGG-19 model results after training . (30 epochs)**

Категорія	precision	recall	f1-score
Normal	0.85	0.94	0.90
Glaucoma	0.9	0.84	0.87
Cataract	1.0	0.97	0.98
Diabetic retinopathy	1.0	1.0	1.0

Source: **compiled by the authors**

Table 6. **VGG-16 model results after training (30 epochs)**

Категорія	precision	recall	f1-score
Normal	0.87	0.76	0.81
Glaucoma	0.63	0.89	0.74
Cataract	0.98	0.75	0.85
Diabetic retinopathy	1.0	0.99	0.99

Source: **compiled by the authors**

High performance indicates their ability to effectively learn and recognise patterns in the data.

– EfficientNet: precision - 0.95, recall - 0.95, f1-score - 0.95.

– VGG-19: precision - 0.94, recall - 0.94, f1-score - 0.94.

– VGG-16: precision - 0.87, recall - 0.85, f1-score - 0.85

After 50 epochs, the models retained high accuracy with minimal changes (Table 7, Table 8 and Table 9), which demonstrates the stability of their performance.

Table 7. **EfficientNet model results after training (50 epochs)**

Категорія	precision	recall	f1-score
Normal	0.95	0.95	0.95
Glaucoma	0.91	0.91	0.91
Cataract	0.94	0.97	0.95
Diabetic retinopathy	1.0	1.0	1.0

Source: **compiled by the authors**

Table 8. **VGG-19 model results after training (50 epochs)**

Категорія	precision	recall	f1-score
Normal	0.94	0.94	0.94
Glaucoma	0.90	0.84	0.87
Cataract	1.0	0.97	0.98
Diabetic retinopathy	1.0	1.0	1.0

Source: **compiled by the authors**

Table 9. **VGG-16 model results after training (50 epochs)**

Категорія	precision	recall	f1-score
Normal	0.87	0.85	0.85
Glaucoma	0.63	0.89	0.74
Cataract	0.98	0.75	0.85
Diabetic retinopathy	1.0	0.99	0.99

Source: **compiled by the authors**

The use of the callback function helped to avoid overtraining and to record the best results.

– EfficientNet: precision - 0.95, recall - 0.95, f1-score - 0.95.

– VGG-19: precision - 0.94, recall - 0.94, f1-score - 0.94.

– VGG-16: precision - 0.87, recall - 0.85, f1-score - 0.85.

The choice of EfficientNet, VGG-19 and VGG-16 models for ophthalmic disease classification is based on their high performance, accuracy and stability during training on different number of epochs. Although such models as Xception, Baseline, MobileNet, DenseNet, InceptionV3 and ResNet50 also demonstrated acceptable results, they were inferior to the selected models in terms of key metrics. The use of the callback function helped to prevent overfitting and allowed us to capture the best results of the models.

These features make EfficientNet, VGG-19 and VGG-16 the best candidates for integration into an ophthalmology diagnostic system, ensuring high accuracy and efficiency in real-world conditions. This, in turn, provides doctors with reliable tools for fast and accurate diagnosis, which will help improve the quality of medical services.

RESEARCH RESULTS

Visualization of a health monitoring algorithm is an important tool for improving understanding, communication, documentation, optimization, and system maintenance. The dataset consisted of fundus images classified into four main categories: cataract, diabetic retinopathy, glaucoma, and healthy eye (Fig. 1). Each image had a corresponding label, which allowed the data to be used to train machine learning models.

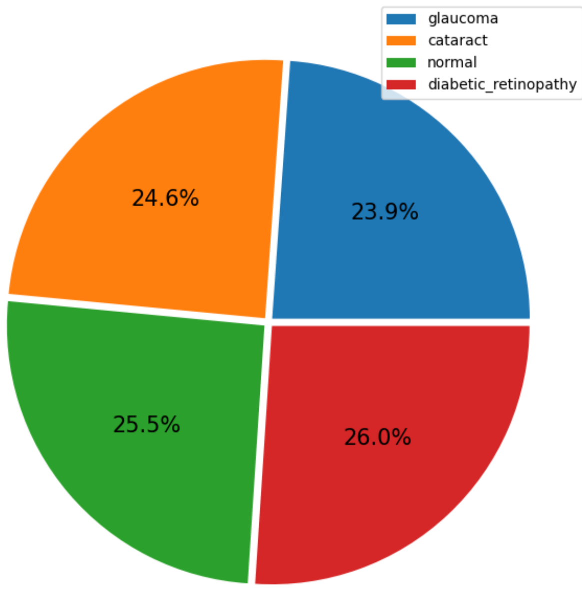


Fig. 1. **Data categorisation**

Source: **compiled by the authors**

Before starting to work with the models, the data was pre-processed to meet the requirements of the machine learning models.

The main steps of the preparation method included:

1. Checking for outliers and anomalies. The data were analysed for missing values, which were either filled in with estimated values or removed. Anomalous values that could reduce the accuracy of the models were identified and handled, in particular by using interquartile range (IQR).
2. Data normalisation. All images were normalised to provide a single scale of values. They were scaled to a size of 224x224 pixels and normalised by dividing each pixel by 255, which is important for the stable operation of neural networks.
3. Data balancing. Since the disease classes had different numbers, balancing methods, such as over- or under-sampling, were used to ensure an even distribution between the classes.
4. Splitting the data into training and test samples. The data were separated for training and testing, which allowed the accuracy of the models to be assessed on independent data.

Careful data preparation – from validation and normalisation to balancing and distribution – is a key step in the development of intelligent medical image classification systems, providing a reliable dataset and increasing the accuracy of machine learning models. This ultimately improves diagnostic accuracy for ophthalmic diseases and increases the quality of medical services.

Fig. 2 shows examples of images for each category (cataract, diabetic retinopathy, glaucoma, and healthy eye) that reflect the diversity and characteristics of each disease, which contributes to the effective training of classification models.

Thus, the comprehensive stages of data collection, processing and analysis ensured high quality and reliability of the dataset, which is critical for accurate prediction of ophthalmic diseases using neural networks.

One of the main functions of the system is the ability to upload eye images for analysis and obtain a disease prediction using various machine learning models. The user can choose one of the models (VGG19, EfficientNet, VGG16) and get results with the specified prediction accuracy.

For example, the user uploads an image of the eye, selects the VGG19 model, and receives a disease prognosis with an accuracy of 93.66 % (Fig.3).

Using the EfficientNet model, the user receives a forecast with an accuracy of 96.94 % (Fig. 4).

When choosing the VGG16 model, the forecast accuracy is 89.09 % (Fig. 5).

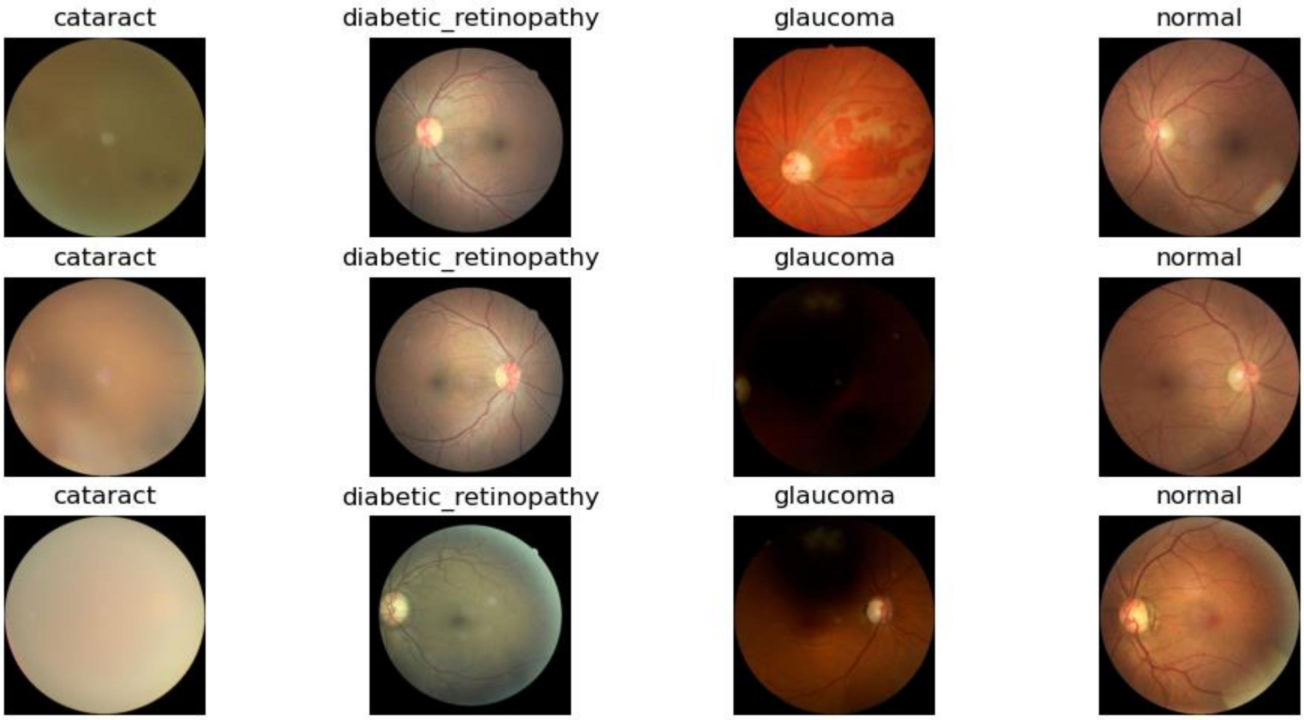


Fig. 2. **Sample images from the dataset**
Source: **compiled by the authors**

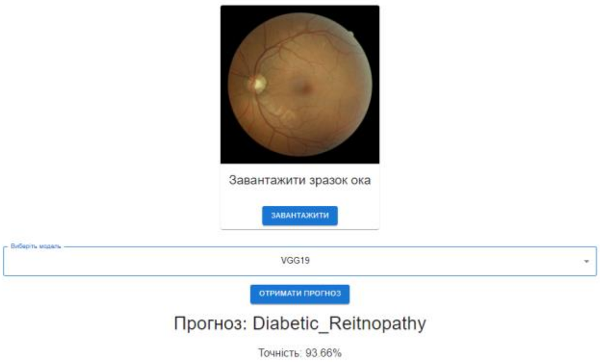


Fig. 3. **Diagnosis of the disease using the VGG-19 model**
***Source:* compiled by the authors**

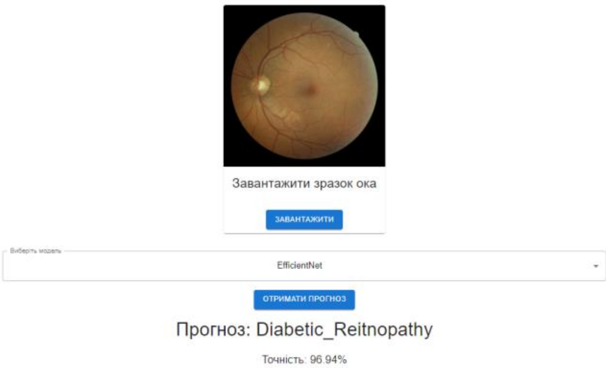


Fig. 4. **Diagnosing a disease using the EfficientNet model**
***Source:* compiled by the authors**

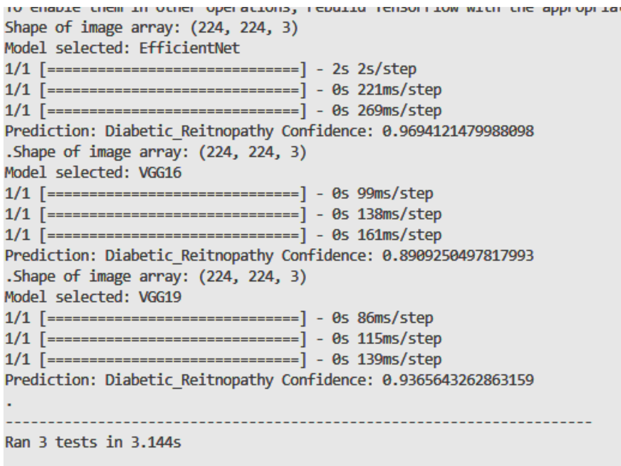
Fig. 5. **Diagnosis of the disease using the VGG-16 model**
***Source:* compiled by the authors**

DISCUSSION OF THE RESULTS

Machine learning models were tested using the unittest framework in Python. The main focus was on checking the correctness of three models: EfficientNet, VGG16, and VGG19.

Fig. 6 shows the accuracy of diabetic retinopathy predictions for each model.

– EfficientNet: prediction accuracy 96.94 %.
– VGG16: prediction accuracy 89.09 %.
– VGG19: prediction accuracy 93.66 %.

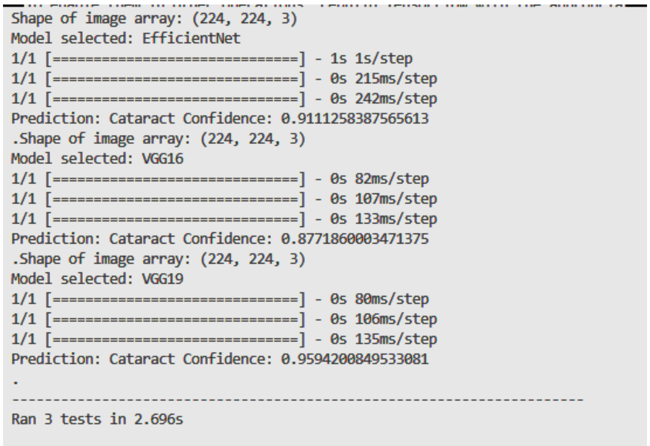


```
Shape of image array: (224, 224, 3)
Model selected: EfficientNet
1/1 [==============================] - 2s 2s/step
1/1 [==============================] - 0s 221ms/step
1/1 [==============================] - 0s 269ms/step
Prediction: Diabetic_Reitnopathy Confidence: 0.9694121479988098
.Shape of image array: (224, 224, 3)
Model selected: VGG16
1/1 [==============================] - 0s 99ms/step
1/1 [==============================] - 0s 138ms/step
1/1 [==============================] - 0s 161ms/step
Prediction: Diabetic_Reitnopathy Confidence: 0.8909250497817993
.Shape of image array: (224, 224, 3)
Model selected: VGG19
1/1 [==============================] - 0s 86ms/step
1/1 [==============================] - 0s 115ms/step
1/1 [==============================] - 0s 139ms/step
Prediction: Diabetic_Reitnopathy Confidence: 0.9365643262863159
.
----------------------------------------------------------------------
Ran 3 tests in 3.144s
```

Fig. 6. **Application of unittest for diabetic retinopathy**
***Source:* compiled by the authors**

The models for cataract disease were tested using the same principle. Fig. 7 shows the accuracy of cataract predictions for each model.

– EfficientNet: 91.11 % prediction accuracy.
– VGG16: prediction accuracy 87.71 %.
– VGG19: prediction accuracy 95.94 %.



```
Shape of image array: (224, 224, 3)
Model selected: EfficientNet
1/1 [==============================] - 1s 1s/step
1/1 [==============================] - 0s 215ms/step
1/1 [==============================] - 0s 242ms/step
Prediction: Cataract Confidence: 0.9111258387565613
.Shape of image array: (224, 224, 3)
Model selected: VGG16
1/1 [==============================] - 0s 82ms/step
1/1 [==============================] - 0s 107ms/step
1/1 [==============================] - 0s 133ms/step
Prediction: Cataract Confidence: 0.8771860003471375
.Shape of image array: (224, 224, 3)
Model selected: VGG19
1/1 [==============================] - 0s 80ms/step
1/1 [==============================] - 0s 106ms/step
1/1 [==============================] - 0s 135ms/step
Prediction: Cataract Confidence: 0.9594200849533081
.
----------------------------------------------------------------------
Ran 3 tests in 2.696s
```

Fig. 7. **Application of unittest for cataracts**
***Source:* compiled by the authors**

The models were also tested for glaucoma. Fig. 8 shows the prediction accuracy for each model.

– EfficientNet: 94.93% prediction accuracy.
– VGG16: prediction accuracy 86.72 %.
– VGG19: prediction accuracy of 96.77 %.

```
Shape of image array: (224, 224, 3)
Model selected: EfficientNet
1/1 [==============================] - 1s 1s/step
1/1 [==============================] - 0s 223ms/step
1/1 [==============================] - 0s 251ms/step
Prediction: Glaucoma: 0.9492982029914856
.Shape of image array: (224, 224, 3)
Model selected: VGG16
1/1 [==============================] - 0s 86ms/step
1/1 [==============================] - 0s 111ms/step
1/1 [==============================] - 0s 135ms/step
Prediction: Glaucoma: 0.86729496717453
.Shape of image array: (224, 224, 3)
Model selected: VGG19
1/1 [==============================] - 0s 92ms/step
1/1 [==============================] - 0s 111ms/step
1/1 [==============================] - 0s 137ms/step
Prediction: Glaucoma: 0.967727541923523
.
----------------------------------------------------------------------
Ran 3 tests in 2.747s
```

Fig. 8. **The use of unittest for glaucoma**
***Source:* compiled by the authors**

These results confirm the high accuracy and reliability of the models for classifying ophthalmic diseases.

The test results confirmed the high efficiency and accuracy of the developed ophthalmic disease classification system using machine learning models.

Thanks to careful data preparation, including data cleaning, normalisation and balancing, the system demonstrated excellent results in classifying diseases such as diabetic retinopathy, cataracts and glaucoma. The use of VGG-16, VGG-19 and EfficientNet models allowed us to achieve high accuracy and confirm the ability of these models to effectively analyse fundus images and make correct predictions.

Testing using the unittest framework in Python showed stable and reliable operation of the system, which is confirmed by the high accuracy of the predictions for each disease. This demonstrates the reliability of the models and their ability to efficiently classify medical images, which, in turn, provides doctors with fast and accurate diagnosis, significantly increasing the efficiency of medical care.

The integration of machine learning into medical practice opens up new prospects for improving the diagnosis and treatment of ophthalmic diseases. This system allows doctors not only to quickly receive the results of medical image analysis, but also to reduce the time for diagnosis, which is especially important for urgent treatment.

CONCLUSIONS

This study demonstrated the effectiveness of machine learning models in the classification of ophthalmic diseases using fundus images. Through comprehensive data preprocessing – including anomaly detection, normalization, balancing, and dataset splitting – high-quality input data were ensured, contributing to the reliability and accuracy of the developed models.

The evaluation of three deep learning models - VGG16, VGG19, and EfficientNet - showed that all models achieved high prediction accuracy, with EfficientNet demonstrating the best overall performance (up to 96.94 % for diabetic retinopathy). The system enables users to upload eye images, select a model, and receive an automated disease prognosis with high precision.

Testing with the Python unittest framework confirmed the stability and robustness of the models, reinforcing their potential application in real-world clinical settings. The results highlight the practical benefits of integrating artificial intelligence into ophthalmology, offering rapid and accurate diagnostic support for medical professionals.

The implementation of such a system can significantly enhance the efficiency of ophthalmic disease detection, reduce diagnostic time, and improve the quality of healthcare services. Future research may focus on expanding the dataset, improving model generalization, and integrating explainable AI techniques to further enhance trust and interpretability in medical decision-making.

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Дослідження ефективності моделей нейронних мереж для побудови класифікатора офтальмологічних патологій

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АНОТАЦІЯ

Це дослідження представляє розробку та оцінку системи на основі машинного навчання для класифікації офтальмологічних захворювань за допомогою фундусних зображень. Набір даних складається з зображень, що поділяються на чотири основні класи: катаракта, діабетична ретинопатія, глаукома та здорова око. Для забезпечення точності та надійності моделей дані пройшли етапи попередньої обробки, включаючи виявлення викидів, нормалізацію, балансування та поділ на тренувальні та тестові набори. Для класифікації захворювань було використано три моделі глибокого навчання: VGG16, VGG19 та EfficientNet. Експериментальні результати показали високу точність передбачень у різних категоріях захворювань, причому EfficientNet досяг найвищих результатів (до 96,94% для діабетичної ретинопатії). Система дозволяє користувачам завантажувати зображення ока, вибирати модель та отримувати діагностичні прогнози з вказаним рівнем точності. Моделі були ретельно протестовані за допомогою фреймворку Python unittest, що підтвердило їхню стабільність і надійність. Результати підкреслюють потенціал машинного навчання для покращення діагностики офтальмологічних захворювань, скорочення часу діагностики та підвищення ефективності прийняття медичних рішень. Інтеграція цих моделей у медичну практику може значно покращити якість медичних послуг та допомогти лікарям надавати більш ефективні та точні діагнози.

Ключові слова: офтальмологічні захворювання; медичні зображення; інтелектуальна система; моделі машинного навчання; ідентифікація і діагностика захворювань

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