COMPARATIVE ANALYSIS OF CNN MODELS FOR CLASSIFICATION OF EYE ABNORMALITIES

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***Abstract*: This study presents a methodology for the comparative analysis of different deep learning models for the detection of eye diseases implemented in the proposed system. Eye abnormalities represent a significant public health challenge globally, necessitating accurate and efficient diagnostic tools for effective treatment and management. This approach involves the usage of a pre-trained Convolutional Neural Networks (CNN) model, namely AlexNet, GoogLeNet, ResNet, ShuffleNet, MobileNetV2, Xception, and VGG-16 for transfer learning. This research investigates the effectiveness of various deep learning models in analyzing ophthalmic images for the classification of abnormalities. This study compares the performance of different models on a labeled dataset of retinal or corneal images containing various conditions. Metrics such as accuracy, sensitivity, and specificity will be employed to assess the models' ability to classify conditions like diabetic retinopathy, glaucoma, Cataracts, Age degeneration, and hypertension. This system can be used as a valuable tool for assisting ophthalmologists, in early abnormalities classification and treatment planning.**

Keywords- Deep Learning, CNN, Comparative Analysis, Diabetic Retinopathy, Glaucoma, Cataracts, Age Degeneration, Hypertension, GoogleLeNet, ResNet18, ShuffleNet, Xception, VGG16, AlexNet, Mobilenet-v2

I. INTRODUCTION

Millions of people worldwide are impacted by eye illnesses, which pose a serious threat to global health by significantly increasing morbidity and blindness. Effective treatment and management of many illnesses depend on a timely and correct diagnosis, but this is still a difficult and frequently labor-intensive undertaking, especially in settings with limited resources. An important component of traditional diagnostic techniques is the manual examination and interpretation by skilled ophthalmologists, which can be laborious, subjective, and prone to error. A new era of automated medical picture analysis has been brought about by the development of deep learning, a branch of artificial intelligence that draws inspiration from the composition and operations of the human brain. CNNs have shown the ability to outperform humans in diagnostic tasks by immediately learning complex patterns and features directly from raw pixel data, promising a more efficient and accurate approach to diagnosing eye abnormalities.

Mohammed Farak (2022**)** has suggested a framework makes a significant advance in that it efficiently assesses the degree of diabetic retinopathy severity while requiring less time and space, indicating that it is a good option for autonomous diagnosis. A hybrid deep convolutional neural network (DCNN) is verified on the APTOS-2019 database, which is accessible to the public, by concatenating the features collected from different layers of the pre-trained XCeption model.

Anila Sebastian et al. (2023) has performed a Survey on Deep-Learning-Based Diabetic Retinopathy Classification. The number of people who have experienced diabetes in the world, has been considerably increasing recently. It affects people of all ages. People who had diabetes for a long time are affected by a disorder called Diabetic Retinopathy (DR), which causes damage to the eyes. Automatic detection using new technologies for early detection can help to avoid complications such as loss of vision. At present, with the advancement of Artificial Intelligence (AI) methodologies, particularly Deep Learning (DL), DL-centric approaches are extensively favored for constructing detection systems for diabetic retinopathy. This research reviews the available literature on diagnosing diabetic retinopathy from fundus images through deep learning and offers a concise overview of current DL methodologies. This study also implemented the usage of AI into Deep Learning effectively and thus obtained accurate results in short duration of time.

Bin Sun (2022) highlighted that Diabetic retinopathy (DR) poses a significant threat to diabetic patients, often resulting in irreversible blindness if left untreated. Despite its severity, DR screening is both time-consuming, requiring skilled ophthalmologists, and prone to misdiagnosis. Recently, there has been a growing focus on leveraging deep learning methods, particularly convolutional neural networks, for medical image analysis, notably in the realm of DR diagnosis.

John Smith et al. (2022) has performed on Deep Learning-based Automated Diagnosis of Diabetic Retinopathy Using Retinal Fundus Images This paper presents a deep learning-based automated system for diagnosing diabetic retinopathy (DR) using retinal fundus images. The proposed system utilizes a convolutional neural network (CNN) architecture trained on a large dataset of annotated retinal images. Experimental results demonstrate the effectiveness of the system in accurately classifying different stages of DR, thus providing a valuable tool for early detection and management of this sight-threatening condition.

Sarah Lee et al. (2021) performed a comparative study on Glaucoma Detection Using Deep Convolutional Neural Networks. This paper further proposed Glaucoma as a leading cause of irreversible blindness worldwide, highlighting the importance of early detection and diagnosis. This study compares the performance of various deep convolutional neural network (CNN) architectures for automated glaucoma detection using optic nerve head (ONH) images. These results demonstrate the efficacy of deep learning approaches in accurately identifying glaucomatous changes, thus offering potential benefits for screening and clinical decision-making in ophthalmology.

The paper titled “Multi-Modal Deep Learning for Age-Related Macular Degeneration Classification Using Optical Coherence Tomography and Fundus Photography”, by Wei Zhang et al. (2021) proposed the usage of various techniques in analyzing ARMD. This study examined Age-related macular degeneration (AMD) as one of the leading cause of vision loss in the elderly population. This paper proposes a multi-modal deep learning framework for classifying AMD using both optical coherence tomography (OCT) and fundus photography images. By integrating information from multiple imaging modalities, our model achieves superior performance in AMD classification compared to single-modal approaches, thereby enhancing diagnostic accuracy and clinical utility.

Fatima Ali et al. (2023) performed an experiment on Classification of Retinal Diseases Using Transfer Learning by implementing Deep learning. Retinal abnormalities encompass a diverse range of pathological conditions, each requiring specialized diagnostic approaches. This work investigated the effectiveness of transfer learning in training deep neural networks and implemented the results by demonstrating the feasibility of leveraging pre-trained models to achieve robust performance across multiple disease categories, paving the way for scalable and cost-effective diagnostic solutions in ophthalmology. Deep Learning requires a lot of data to train and it may require a lot of time and memory as well but this is an efficient method once the neural network model is trained of the data set completely.

The paper titled “Automated Detection of Diabetic Macular Edema Using Deep Learning and Optical Coherence Tomography" by Yu Chen et al (2023) examined Diabetic macular edema (DME) as a common complication of diabetic retinopathy and a leading cause of vision loss among diabetic patients.

This paper presents an automated system for DME detection using deep learning techniques applied to optical coherence tomography (OCT) images. Most of the deep neural network model demonstrates high sensitivity and specificity in identifying DME-associated features, offering potential benefits for timely intervention and management of this sight-threatening condition.

Hua Wang et al. (2019) has performed a classification on Deep Learning-Based Classification of Retinopathy of Prematurity Using Wide-Field Retinal Images. Retinopathy of prematurity (ROP) is a significant cause of childhood blindness, necessitating early detection and treatment to prevent visual impairment. The Early Treatment for Retinopathy of Prematurity study established numerous significant epidemiological risk factors for ROP. This trial, conducted as a randomized, prospective multicenter study, examined the safety of ablating the peripheral retina at earlier versus conventionally timed intervals. This study proposes a deep learning-based approach for ROP classification using wide-field retinal images. By leveraging the spatial information provided by wide-field imaging and this model achieves accurate classification of ROP severity, thus facilitating timely referral and intervention for affected infants.

Xiaoyu Li et al. (2020) performed an experiment on the Integration of Clinical Data with Deep Learning for Improved Diagnosis of Ocular Surface Diseases. This condition encompasses a spectrum of conditions affecting the cornea, conjunctiva, and tear film, posing diagnostic challenges due to overlapping clinical features. This work proposes a novel approach that integrates clinical data with deep learning algorithms for enhanced diagnosis of ocular surface diseases. By leveraging both quantitative imaging features and subjective clinical assessments. This model achieves improved accuracy in disease classification, thereby aiding clinicians in making informed diagnostic and therapeutic decisions.

Mahmoud Smaida et al. (2019) have performed several techniques for the advancement in the Development of Neural Network Algorithms for the Automation of Early Diagnostics of Eye Diseases (GMD system). This study focuses on utilizing deep learning techniques for the early diagnosis of eye abnormalities, particularly Diabetic Retinopathy, Glaucoma, Myopia, and Normal cases. It introduces the concept of a confusion matrix to evaluate the performance of three different neural network architectures: CNN, VGG16, and InceptionV3. This research emphasizes the importance of accurately assessing classifier performance, especially in scenarios with unequal class distributions or multiple classes. By comparing the classification accuracies of the three models, the study concludes that the InceptionV3 model yields the highest accuracy (81.00%), outperforming the other architectures.

II. METHODOLOGY

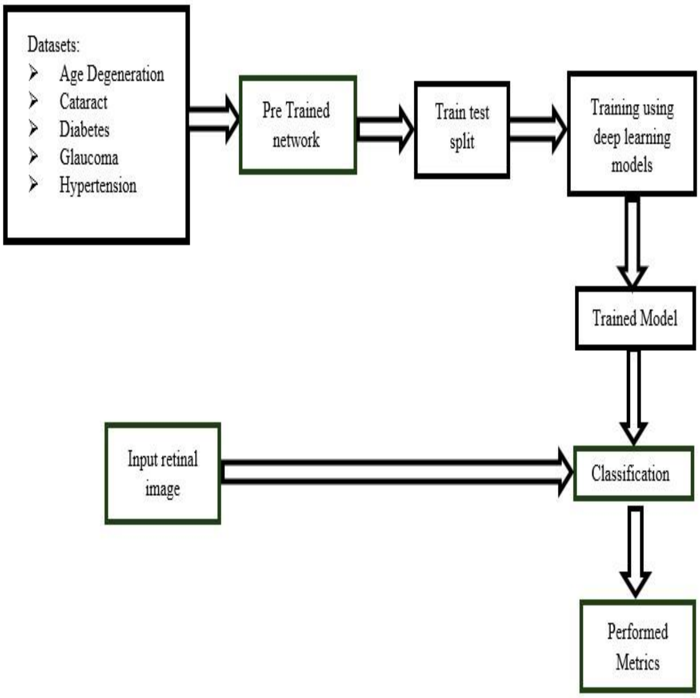

Fig 1. Block Diagram

The system utilizes curated datasets of retinal or fundus images, labeled with corresponding disease categories. A suitable pre-trained CNN model is initialized to leverage its learned features. The dataset is split into training and testing sets for model training and evaluation. Transfer learning is applied to fine-tune the pre-trained model on the specific eye disease dataset, enhancing its accuracy. Following training, the model is employed to classify unseen retinal images, and its performance is evaluated using a separate validation dataset, with optimization techniques applied for further refinement.

ALGORITHM:

AlexNet: AlexNet is a pioneering eight-layer convolutional neural network, known for its role in advancing deep learning. It revolutionized image classification by significantly reducing error rates on the ImageNet dataset. The pre-trained version, trained on over a million images from ImageNet, offers a robust foundation for various computer vision tasks, including object recognition and feature extraction.
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GoogleLeNet: A convolutional neural network with 22 layers is called GoogLeNet. The network can be loaded in a pre-trained state using the Places365 [2] [3] or ImageNet [1] data sets. With the help of ImageNet, the network was trained to classify photos into 1000 object categories.

MobileNetV2: A convolutional neural network with 53 layers is called MobileNet-v2. A pretrained version of the network, trained on over a million photos from the ImageNet collection, is available for download [1]. The pre-trained version, trained on ImageNet, is suitable for resource-constrained environments, making it ideal for mobile applications and edge devices

ResNet18: ResNet18, part of the ResNet (Residual Network) family, features 18 layers and employs residual connections to facilitate the training of very deep networks. It addresses the vanishing gradient problem by introducing skip connections, enabling the network to learn residual mappings effectively. The pre-trained model, trained on ImageNet, offers a strong foundation for various image classification tasks, with improved training convergence and accuracy compared to traditional architectures.

ShuffleNet: ShuffleNet is tailored for deployment on resource-constrained mobile devices, emphasizing efficiency without compromising accuracy. It introduces novel techniques like pointwise group convolution and channel shuffle to minimize computational costs. These innovations enable ShuffleNet to achieve high performance while maintaining low memory and power requirements, making it well-suited for edge computing and mobile applications.

VGG16: VGG16, a variant of the VGG model, is renowned for its simplicity and effectiveness. With 16 convolutional and fully connected layers, it offers a straightforward yet powerful architecture for image classification tasks. Despite its simplicity compared to newer models, VGG16 remains a popular choice due to its ease of understanding and strong performance on various datasets.

Xception: Xception, an extension of the Inception architecture, replaces traditional Inception modules with depthwise separable convolutions. This modification enhances the model's efficiency and reduces computational costs, making it suitable for deployment on resource-constrained platforms. Xception achieves state-of-the-art performance with a lightweight serialization of less than 91MB, making it ideal for applications where both accuracy and efficiency are crucial considerations.

III. RESULTS AND DISCUSSION

A dataset comprising 1372 retinal images across five categories of eye diseases was collected from Kaggle. The categories include cataracts (292 images), Age degeneration (265 images), diabetic retinopathy (405 images), glaucoma (127 images), and hypertension (127 images). MATLAB, known for its robust image classification capabilities and seamless integration with deep learning frameworks, was chosen for the analysis. The dataset was divided into training and validation sets, with 60% (823 images) allocated for training and 40% (548 images) for validation. Neural networks were trained using stochastic gradient descent with momentum (SGDM) optimization algorithm with an initial learning rate of 0.001. The training options are tailored for each model architecture to achieve optimum performance. Following training, the models were tested using separate test images. Finally, the input image along with its predicted class label is displayed in a separate window allowing for visual inspection of the predicted outcome

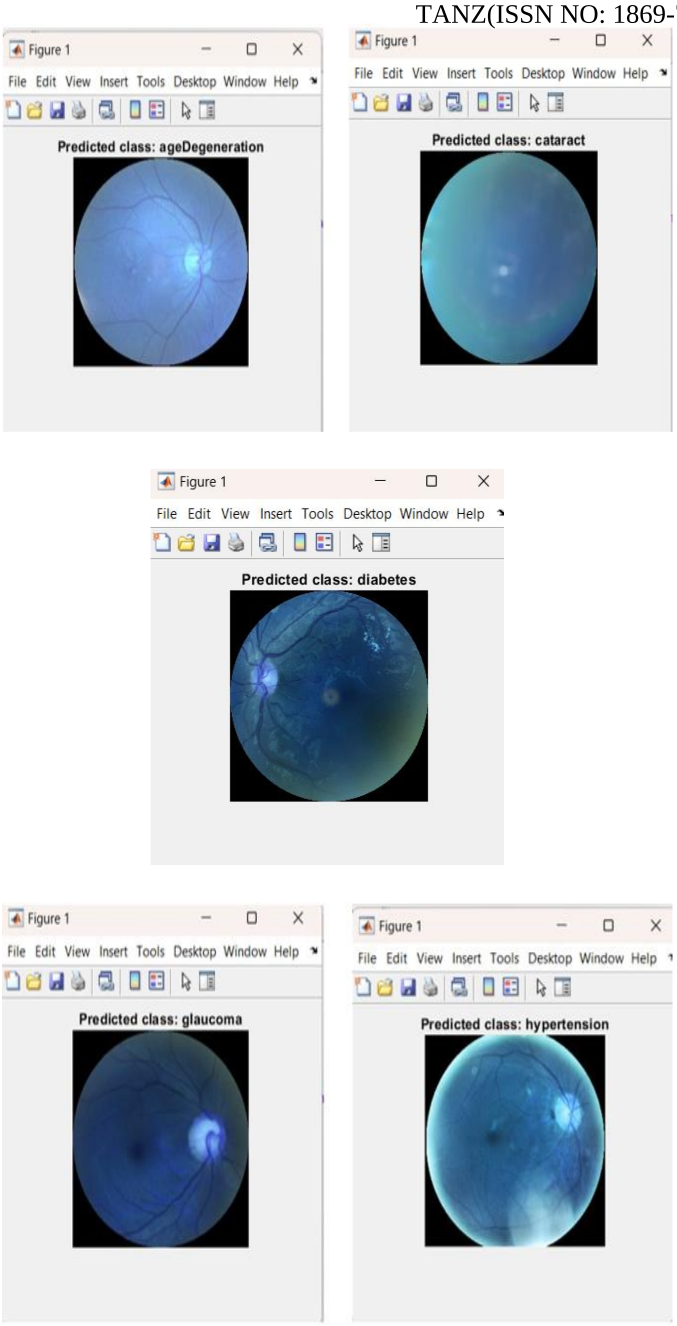

Fig 2. Display of test results

The accuracy values from the training progress graphs for all seven models are tabulated, providing insights into their performance on both training and validation datasets.

Table I
Accuracy of the CNN models

CNN MODEL	TRAINING ACCURACY	VALIDATION ACCURACY
GoogLeNet	97.10	67.45
ResNet18	96.74	65.09
ShuffleNet	95.89	62.18
VGG16	96.74	67.64
Xception	85.49	65.64
MobileNet-v2	92.38	61.45
AlexNet	88.56	61.59

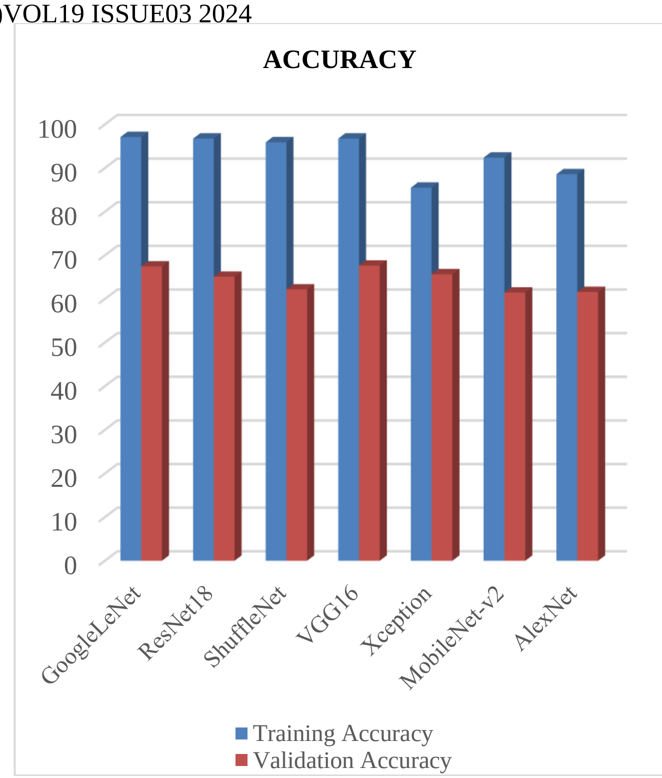

Fig 3. Graphical representation of accuracy values of all models (in percentage)

The confusion matrices for all seven models were generated, serving as the basis for calculating performance metrics including precision, recall, specificity, misclassification and F1 score. These metrics provide a comprehensive evaluation of the models' classification performance across training and validation datasets, facilitating comparative analysis.

Table II
Comparative analysis of performance metrics of the CNN models for the training set

CNN Model	Precis i-on	Recall	Specifi -city	F1 Score	Misclassi -fication
ResNet18	0.951	0.822	0.8995	0.953	0.1498
GoogLeNet	0.9716	0.9731	0.9926	0.7802	0.0115
ShuffleNet	0.9675	0.9396	0.9910	0.9528	0.0163
VGG16	0.965	0.9648	0.9908	0.9634	0.0166
Xception	0.8983	0.8276	0.9603	0.8473	0.0556
MobileNet -v2	0.9354	0.902	0.9799	0.9157	0.0302
AlexNet	0.9245	0.8431	0.9938	1.0741	0.0463

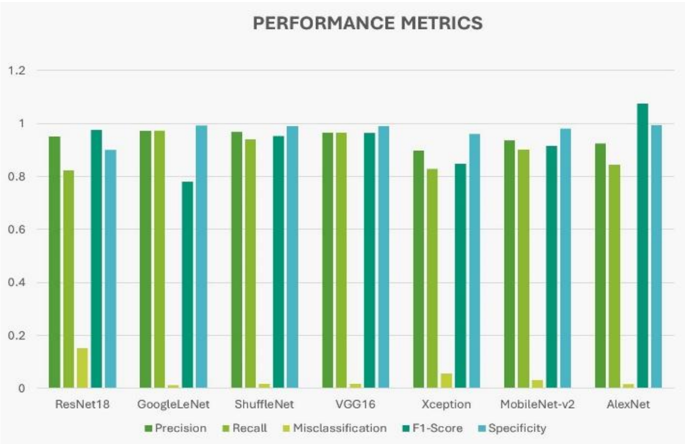

Fig 4. Graphical representation of performance metrics over the performance set

Table III
Comparative analysis of performance metrics of the CNN models for the validation set

CNN Model	Precis-ion	Recall	Specif-icity	F1 Score	Misclassi-fication
ResNet18	0.6217	0.5958	0.9087	0.5999	0.2459
GoogleLe-Net	0.6513	0.6295	0.9255	0.6195	0.1316
ShuffleNet	0.5754	0.5719	0.9008	0.5707	0.1517
VGG16	0.6021	0.7152	0.8826	0.6408	0.1235
Xception	0.6758	0.5622	0.9072	0.5661	0.3538
MobileNet-v2	0.5261	0.5876	0.8875	0.5265	0.1528
AlexNet	0.6334	0.5366	0.7855	0.5496	0.1579

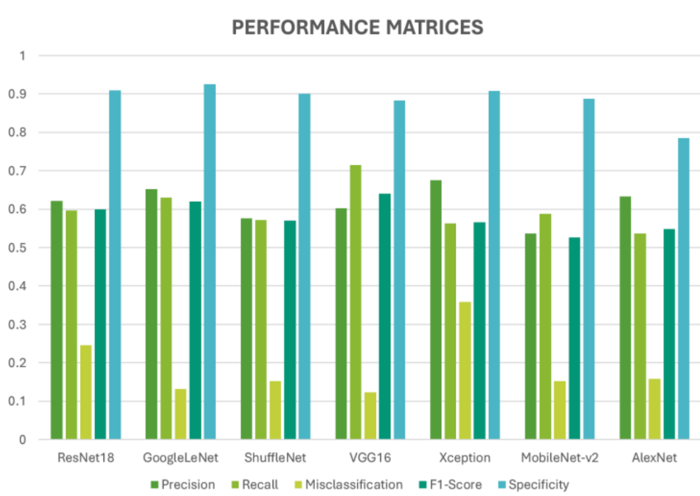

Fig 5. Graphical representation of performance metrics over the performance set

IV. CONCLUSION AND FUTURE WORK

In recent years, significant advancements in medical imaging have spurred the development of numerous models for classifying eye diseases. This project contributes to this progress by conducting a comprehensive comparative analysis of seven CNN models for the classification of various eye diseases using deep learning techniques. Among the 7 models GoogleLeNet emerged as the most favorable choice based on a comprehensive analysis of training and validation metrics. GoogleLeNet's strengths lie in its superior validation performance indicating a better ability to handle unseen data, crucial for real-world applications. It also demonstrates a good balance between precision and recall in validation metrics, suggesting it can accurately identify both positive and negative cases. Additionally, GoogleLeNet's high training accuracy implies a strong learning capability on the training data. This, coupled with a reasonable validation accuracy, suggests it might have learned relevant features for the eye disease classification task. Other models such as VGG16 and ResNet18 might be suitable depending on specific needs. If a large training dataset is available and overfitting can be addressed, ResNet18 could be a strong contender with its high training accuracy and decent validation F1 score. Conversely, if prioritizing high recall for identifying positive cases VGG16 might be an option due to its high recall. However, limitations include a small dataset size of 1372 images, imbalanced datasets, and concerns about overfitting. Future work should focus on incorporating larger and more diverse datasets, addressing class imbalance, exploring newer CNN architectures, employing ensemble learning methods, and integrating explainable AI techniques. These advancements can enhance model accuracy, reliability, and usability in medical applications, facilitating improved diagnosis and treatment of eye diseases.

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