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Clinical Insights through Xception: A Multiclass Classification of Ocular Pathologies

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Abstract: In this study, the Xception convolutional neural network is employed to categorize four distinct eye conditions: cataract, diabetic retinopathy, glaucoma, and normal eye status. The model achieves an impressive accuracy rate of 92.87% when assessed on a dataset comprising 4,127 images. This success highlights the potential of deep learning techniques in the field of ophthalmology, providing a dependable method for early diagnosis and disease management. Based on these promising outcomes, the research outlines several prospective directions, including model refinement, transfer learning, multiclass classification, data augmentation, ensemble learning, interpretability, clinical integration, ethical considerations, and diversification of the dataset. These paths hold the potential to further enhance the capabilities of AI-based diagnostic systems in ophthalmology, contributing to improved patient care and early intervention, all while addressing ethical and practical concerns within the healthcare domain.

Keywords: *Xception, Ophthalmology, Cataract, Diabetic Retinopathy, Glaucoma.*

1. Introduction

The human eye is an intricate sensory apparatus, consisting of the cornea, lens, retina, and optic nerve, with the primary function of capturing and conveying visual data to the brain for processing and comprehension [1]. Eye disease pertains to a medical ailment that impacts the eyes, encompassing a broad spectrum of disorders, including conditions like glaucoma, cataracts, and macular degeneration [2]. These ailments have the potential to lead to compromised vision or even complete loss of sight. Machine learning represents a subset of artificial intelligence (AI) that focuses on machines emulating intelligent human behaviors, while image processing serves as a signal processing technique employed to extract information from visual data [3]. Convolutional Neural Networks (CNNs) are deep learning systems primarily utilized for tasks at the pixel level and are the preferred choice for object recognition [4]. Machine learning algorithms have displayed significant potential in the precise identification of a range of ocular conditions, including glaucoma, macular degeneration, and diabetic retinopathy [5]. Research endeavors have employed a variety of algorithms, including Random Forest Classifier, Naïve Bayes, Decision Trees, and Neural Networks, to attain highly accurate disease detection [6]. Promptly detecting and providing efficient care for eye disorders play a critical role in averting vision impairment and enhancing one's overall well-being. Nevertheless, traditional diagnostic approaches, which heavily depend on clinical proficiency, are susceptible to errors. Notable age-related eye ailments encompass diabetic retinopathy (DR), glaucoma, cataracts, and age-related macular degeneration (AMD). It is estimated that by the year 2030, the worldwide incidence of DR cases may escalate to 191.0 million owing to an increase in the prevalence of diabetes [7]. Numerous recent research endeavors have been directed towards the utilization of Deep Learning methods for enhancing the categorization of eye disorders. The authors of this study were inspired by these benefits to create a system called CNN-MDD (Convolutional Neural Network-based Multiple Disease Detection). In this system, the network's effectiveness is significantly influenced by the selection of CNN hyperparameters. The challenge lies in finding the right balance between a smaller learning rate, which may risk losing critical information, and a higher learning rate, which could result in rapid model convergence. This underscores the significance of optimizing CNN hyperparameters to improve training and overall performance [8].

The objective of this research is to introduce a method for categorizing eye conditions such as glaucoma, cataract, diabetic retinopathy, and healthy eyes through the application of Deep Learning. The rest of the paper is structured as follows: Section 2 provides an overview of previous research, Section 3 explains the methodology employed in this study, Section 4 showcases the research findings and insights, and finally, Section 5 concludes the entire study by providing a summary and discussing potential directions for future research.

2. Literature Review

2.1 Cataract

Cataracts primarily form due to the aging process, which impacts the crystalline lens, a distinctive anatomical structure that undergoes continuous growth throughout an individual's lifetime [9]. The transparency and optical clarity of this lens rely on a complex interplay of factors, encompassing its microscopic composition and chemical constituents. Nevertheless, as people age, the lens accumulates yellow-brown pigment and undergoes structural changes in its fibers. This ultimately leads to reduced light transmission and disturbances in its typical architecture, resulting in a decline in optical clarity [9]. Hongyan Zhang and colleagues [10] introduced an innovative cataract grading system comprising six levels. This method incorporates multi-feature fusion by combining high-level attributes extracted from a ResNet18 network with texture characteristics obtained through the gray level co-occurrence matrix (GLCM). It employs two support vector machine (SVM) classifiers as foundational learners to generate probability outputs. Furthermore, a fully connected neural network (FCNN) serves as a meta-learner to produce the final classification outcome, consisting of two fully-connected layers. This approach achieved an average accuracy of 92.66% for six-level grading, with the highest accuracy reaching 93.33%. It also attained an accuracy of 94.75% for four-level grading, surpassing existing methods by a margin of at least 1.75% [10]. Li and coauthors [11] have created an automated system called the Automatic Grading of Nuclear Cataract (AGNC). This system utilizes slit lamp image analysis and comprises three primary components: feature extraction, grade prediction through Support Vector Machine (SVM) regression, and structure detection. AGNC has achieved substantial success rates, with 95% accuracy in lens structure detection and localization, and an impressive 96.9% accuracy. When compared to human graders' classifications based on the Wisconsin cataract grading system, AGNC has shown grading discrepancies of less than one grade for over 97.5% of the evaluated images [11]. The suggested method utilizes transfer learning by leveraging a pre-trained convolutional neural network (CNN) to automate cataract classification. In this approach, the pre-trained CNN model is used for feature extraction, and these features are then fed into a support vector machine (SVM) classifier [12]. Ophthalmologic experts have categorized fundus cataract images into four stages. This method has achieved an accuracy of 92.91% in the classification of these four stages. Additionally, there is an integrated image quality selection module that evaluates the image quality for diagnostic purposes, emphasizing the importance of image quality in CNN-based analysis [12].

2.2 Glaucoma

Glaucoma, the leading cause of global visual impairment without a cure, can result in permanent blindness if not detected early, yet timely recognition allows for preventive measures to avert vision loss, and its prevalence has notably risen, even in urban areas, in recent times [13]. In a study led by Qaisar Abbas, an unsupervised convolutional neural network (CNN) architecture was utilized to extract features, followed by the application of a deep-belief network (DBN) model to select meaningful deep features based on annotated training data; the Glaucoma-Deep system achieved outstanding results when tested on 1200 retinal images from various datasets, demonstrating an average sensitivity (SE) of 84.50%, specificity (SP) of 98.01%, accuracy (ACC) of 99%, and precision (PRC) of 84%, surpassing existing systems and showing promise for large-scale eye-screening in glaucoma identification [14]. In a research study led by Ramgopal and colleagues [15], they conducted an investigation where they employed a deep learning algorithm utilizing a glaucoma dataset. This algorithm integrated pretrained transfer learning models with the U-Net architecture for the segmentation of the optic cup. They utilized the DenseNet-201 deep convolution neural network (DCNN) for feature extraction to determine the presence of glaucoma in retinal fundus images. Their objective was to identify glaucoma and, during training, achieved an accuracy of 98.82%, with a testing accuracy of 96.90%, showcasing superior performance in comparison to existing convolution neural network classification methods rooted in deep learning [15]. In the context of diagnosing glaucoma through the analysis of retinal fundus images, Diaz-Pinto and their team [16] utilized five ImageNet-trained models, namely VGG-16, VGG-19, ResNet50, Inception-v3, and Xception. During testing on five publicly accessible glaucoma datasets, the Xception model exhibited superior performance and efficiency when compared to the other models [16]. Uneja and colleagues presented an artificial intelligence glaucoma expert system that focuses on segmenting the optic cup and disc [17]. They utilized a deep learning framework with a core convolutional neural network (CNN). This system integrated two neural networks to segment images of the optic disc and cup captured by different cameras, resulting in a 93% accuracy in cup segmentation and a 95.8% accuracy in disc segmentation when assessed with 50 images. This advancement facilitates the automated identification of glaucoma [17].

2.3 Diabetic Retinopathy

Diabetic Retinopathy (DR) is a chronic eye condition closely linked to diabetes, serving as the primary cause of vision impairment in the global working-age adult population and potentially impacting over 93 million individuals, where timely detection is critical to slowing or managing progression to vision impairment, yet this proves challenging due to the condition's tendency to manifest minimal symptoms until treatment becomes less effective [18]. As per the findings by Quang and colleagues, the automated diabetic retinopathy (DR) screening approach outlined in this study holds promise for expediting the detection and decision-making procedures, thereby aiding in the management of DR progression [18]. The approach incorporates machine learning models such as CNN, VGG-16, and VGG-19 to analyze fundus images with varying lighting conditions and fields of view, yielding classification results with 80% sensitivity, 82% accuracy, 82% specificity, and a 0.904 AUC across five categories, ranging from 0 (no DR) to 4 (proliferative DR) [18]. Akhilesh Kumar Gangwar and Vadlamani Ravi applied transfer learning by utilizing the pre-trained Inception-ResNet-v2 model and integrated a customized set of CNN layers on top of it to develop a hybrid model [19]. They evaluated the performance of their model using both the Messidor-1 diabetic retinopathy dataset and the APTOS 2019 blindness detection Kaggle dataset, achieving superior results compared to previously reported findings, with a testing accuracy of 72.33% on Messidor-1 and 82.18% on the APTOS dataset [19]. Butt and colleagues [20] have introduced an innovative approach for detecting and categorizing Diabetic Retinopathy in fundus images. Their method incorporates transfer learning (TL) using pre-trained Convolutional Neural Network (CNN) models to extract features, which are then combined into a hybrid feature vector. This feature vector is subsequently fed into various classifiers for both binary and multiclass classification of fundus images, resulting in significant improvements in performance for DR detection. The proposed modified method achieved the highest accuracy, reaching 97.8% for binary classification and 89.29% for multiclass classification when compared to recent approaches [20].

2.4. Xception

The Xception architecture is a convolutional neural network that came to light in 2016 by François Chollet of Google Inc. designed for computer vision applications [21]. It employs depth wise separable convolutions, which split standard convolutions into depth wise and pointwise convolutions, reducing parameters and enhancing efficiency. This innovative approach has made a substantial contribution to the field of image recognition and has inspired the creation of more streamlined neural network architectures. It excels in image classification tasks, often outperforming other models on datasets like ImageNet [22]. In the field of computer vision, it has been adopted as a backbone network for object detection [23] and semantic segmentation tasks [24], contributing to improved accuracy. Additionally, Xception has been applied to medical imaging, aiding in tasks such as tumor detection and disease classification, showcasing its versatility and effectiveness in diverse applications within the realm of deep learning [25].

3. Methods

3.1. Proposed Approach

The Xception [21] architecture was used in this study. The Xception architecture, composed of 71 layers, utilizes depth-wise separable convolutions that separate standard convolutions into depth-wise and pointwise convolutions, effectively reducing model parameters and improving computational efficiency. Conventional convolutional operations amalgamate calculations involving channels and spatial dimensions in one step, whereas Depth-wise Separable Convolution divides this operation into two separate stages. First, it applies a single convolutional filter separately to each input channel, which is the depth wise convolution. Subsequently, it employs pointwise convolution to produce a linear combination of the results generated through the depth-wise convolution [26].

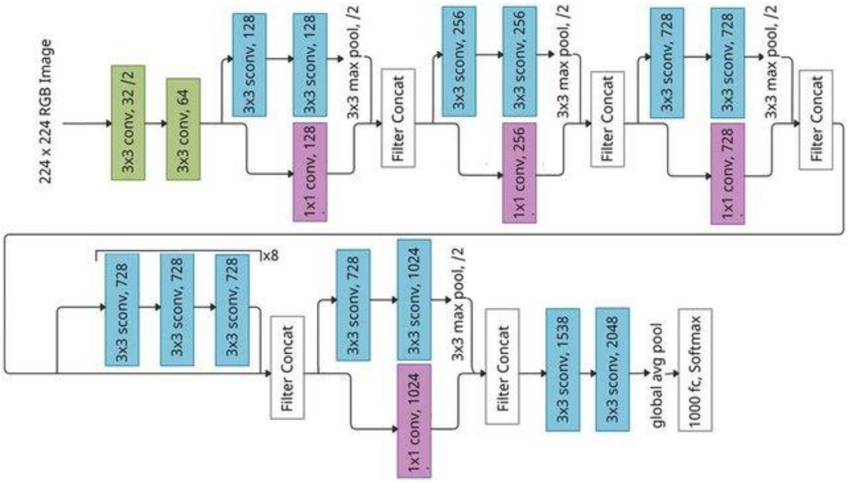

Fig. 1. Structure of Xception [27]

Xception was implemented by transfer learning method in this study. One dense layer with 1024 neurons with ReLu [28] activation function was added to the model. The final output layer had 4 neurons with softmax [29] activation function. While compiling the model adam's optimizer [30] was used as optimizer, categorical crossentropy [31] was used a loss function and the accuracy was used as metrics. Table 1 depicts the parameter distribution of the compiled model.

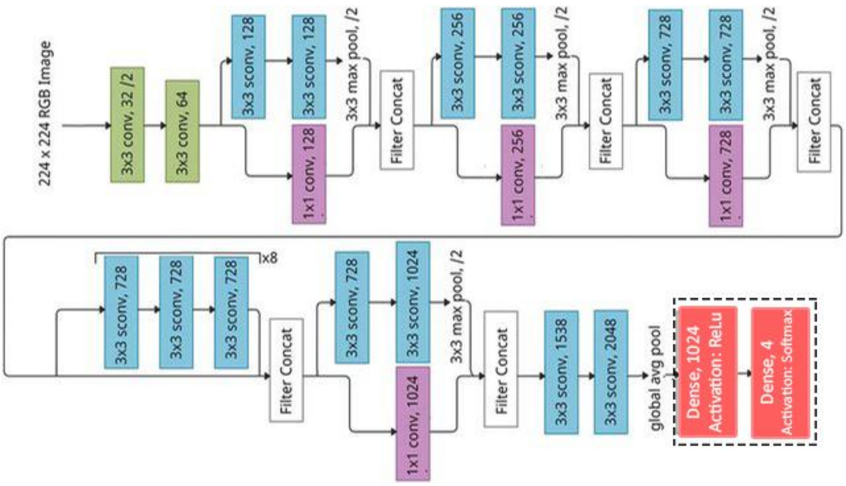

Fig. 2. Proposed Model.

The Rectified Linear Unit, denoted as ReLU, is a widely used activation function in artificial neural networks [28]. Its primary function is to introduce non-linearity by allowing a neuron's output to be the maximum value between 0 and the weighted sum of its inputs. This functionality empowers the model to acquire intricate data patterns and representations, contributing to its widespread adoption in the field. The mathematical formula is expressed in eq (1),

$$f(x) = max(0, x) (1)$$

where x is the input to a neuron.

The Softmax function, as referenced in [29], is a commonly utilized activation function in the field of machine learning, especially in situations that entail multi-class classification. Its primary function revolves around the conversion of a real-number vector into a probability distribution. This transformation assigns distinct probability values to each class, with higher probabilities denoting a stronger likelihood. Consequently, this facilitates the model's capability to make informed class predictions by relying on these calculated probabilities. The mathematical formula is expressed eq (2),

$$S(y)_i = \frac{\exp(y_i)}{\sum_{j=1}^{n} \exp(y_j)} \quad (2)$$

where y represents the input vector; yi represents the i-th element of the input vector and n represents the number of classes.

Table 1. Parameter distribution by the proposed model

Indicators	Number of Parameters
Total Params	22,963,756
Trainable Params	22,909,228
Non-trainable Params	54,528

3.2. Dataset

The dataset employed in this research was a open access dataset gathered from the Kaggle platform [32]. The dataset comprises retinal images categorized into four classes: Normal, Diabetic Retinopathy, Cataract, and Glaucoma. Each class contains approximately 1000 images, which have been gathered from diverse sources such as IDRiD [33], Ocular Recognition [34], HRF [35], and others.

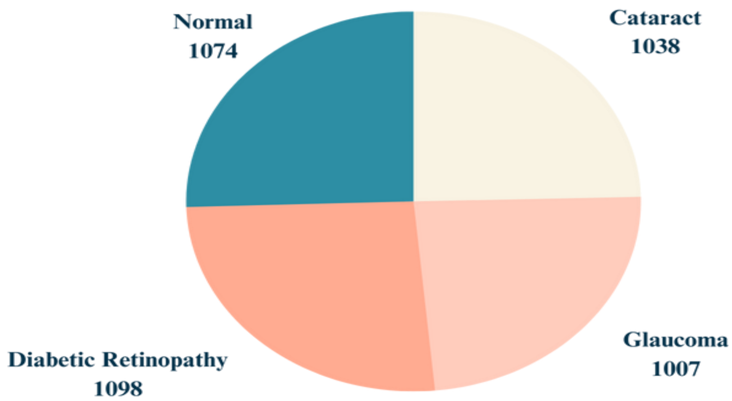

Fig. 3. The distribution of data among different classes in the dataset.

Seventy-five percent of the dataset was allocated for training, while fifteen percent was reserved for validation, and the remaining ten percent was set aside for testing purposes. The dataset distribution is represented in Fig.4.

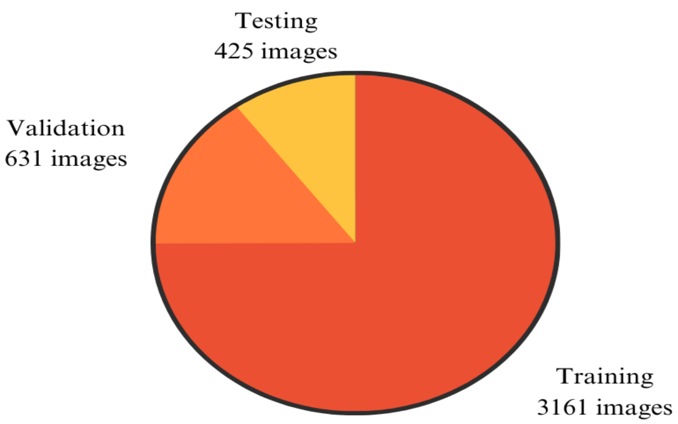

Fig. 4. Dataset distribution in training, validation, and testing data.

3.3. Data Pre-processing

The data was pre-processed before the training phase in order to get an expected result in the training phase. Initially, the dimensions of the initial image were decreased from 512x512 to 128x128. Images were randomly rotated by 40 degrees, zoom and shear transformation was used and newly created pixels were filled after transformations. Random operations such as horizontal flipping, as well as adjustments in width and height, were applied to the images. The labeling of the pre-processed data was carried out using TensorFlow's ImageDataGenerator [36]. The pixel values underwent rescaling to fall within the range of [0,1].

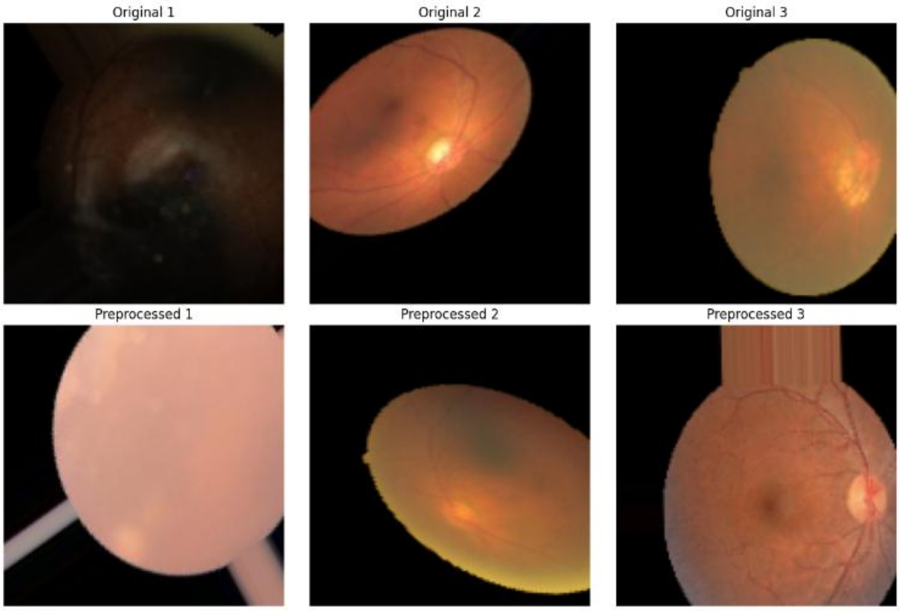

Fig. 5. Original vs Pre-Processed images.

3.4. Training the Model

The model was trained on google colaboratory where there is 12.7 GB System RAM and 15 GB GPU RAM [37]. The model was trained for 30 epochs. The weights and checkpoints from every epoch were recorded and saved for detailed investigation.

4. Results

4.1 Model Evaluation

The model achieved a training accuracy of 95.29% following 28 epochs with a learning rate of 0.001. Additionally, the validation accuracy reached 92.87%, and the test accuracy was measured at 91.29%. The training and validation curve is depicted below:

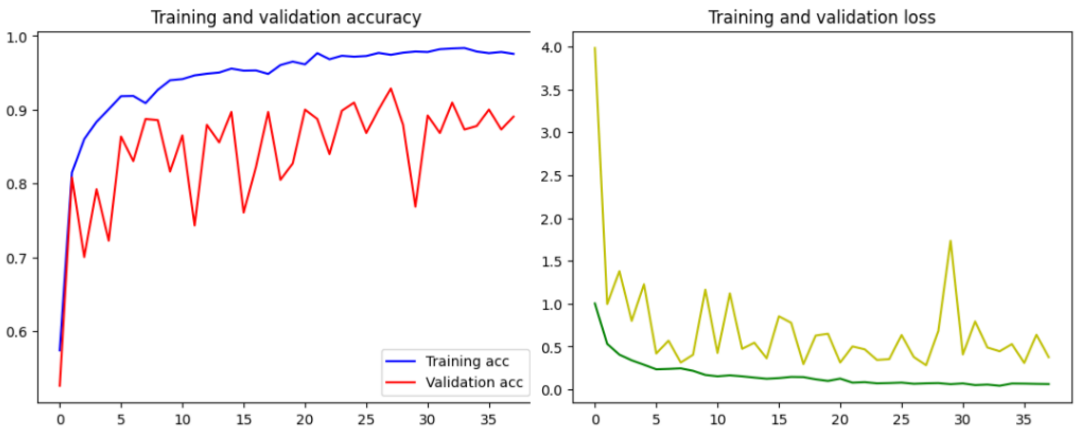

Fig. 6. The Curve Displaying Accuracy and Loss for the model under consideration

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A confusion matrix is a statistical instrument utilized in machine learning and classification endeavors to assess the effectiveness of a predictive model [38]. It furnishes a structured representation of the model's forecasts compared to real results, classifying them into four groups: true positives (accurate positive predictions), true negatives (precise negative predictions), false positives (inaccurate positive predictions), and false negatives (inaccurate negative predictions). It plays a crucial role in evaluating a model's accuracy, precision, recall, and F1-score, providing practitioners with the means to measure the efficiency of the models.

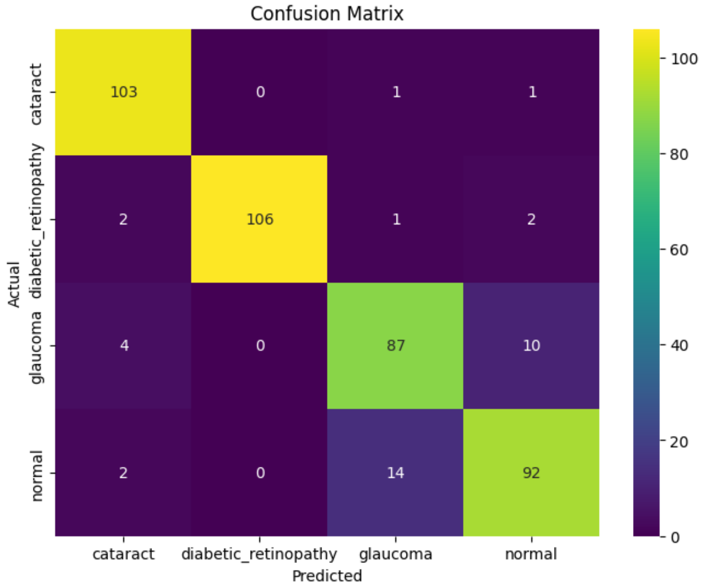

Fig. 7. Confusion Matrix of the approached model

Precision evaluates the precision of a model's positive predictions, recall measures its capability to include all pertinent positive instances, and the F1-score represents the harmonic average of precision and recall, offering a well-rounded assessment of a model's binary classification task performance [39], [40]. The mathematical representation of precision, recall and F1-score is represented in Eq. (3), (4), (5),

$$\text{Precision}=\frac{TP}{TP+FP} \quad (3)$$

$$\text{Recall}=\frac{TP}{TP+FN} \quad (4)$$

$$\text{F1 Score} = \frac{TP}{TP+\frac{1}{2}(FP+FN)} \quad (5)$$

where TP represents True Positive; FP represents False Positive; FN represents False Negative.

The classification report containing class-wise precision, recall and F1-score is highlighted in the table 2.

Table 2. An evaluation report detailing the classification performance of the proposed model

Classes	***Precision***	***Recall***	***F1-Score***
Cataract	0.93	0.98	0.95
Diabetic Retinopathy	1.00	0.95	0.98
Glaucoma	0.84	0.85	0.85
Normal	0.88	0.86	0.86

4.2. Discussion

Based on the confusion matrix depicted in Figure 7, it is evident that the model accurately predicts 103 out of 105 cases of cataract, 106 out of 111 cases of Diabetic Retinopathy, 87 out of 101 cases of Glaucoma, and finally, 92 out of 108 cases of normal eyes. It's worth mentioning that the mean values for precision, recall, and F1-score were consistent, registering at 0.91.

5. Conclusion

In summary, the utilization of the Xception convolutional neural network for the classification of cataract, diabetic retinopathy, glaucoma, and normal eye conditions has yielded notable results. The model achieved an impressive accuracy rate of 92.87% when evaluated on a dataset containing 4,127 images distributed across these four distinct classes. These results underscore the promise of employing deep learning methods in the realm of ophthalmology, offering a reliable and effective avenue for expediting the early detection and management of ocular disorders. As we continue to harness the capabilities of advanced neural networks and make use of comprehensive datasets, like the one available on Kaggle, the future holds the promise of significant advancements in healthcare outcomes and the early detection of eye conditions, ultimately improving the quality of life for individuals affected by these ailments.

The prospects within this domain encompass several avenues for improvement and innovation. Firstly, there is room for further refinement and optimization of the Xception model, coupled with meticulous fine-tuning of hyperparameters, to elevate both its classification accuracy and operational efficiency. Furthermore, delving into advanced methods such as transfer learning with larger and more varied datasets has the potential to expand the model's proficiency, allowing it to classify a wider range of eye-related conditions. Moving from binary to multi-class classification can provide a more detailed level of diagnostic precision, and the incorporation of data augmentation techniques can strengthen the model's robustness.

To enhance overall performance and establish greater transparency and trustworthiness for clinical integration, strategies such as ensemble learning approaches and interpretability tools can be employed. Furthermore, it is imperative to address ethical considerations, ensure adherence to regulatory standards, and diversify the dataset comprehensively. These steps are essential for advancing the practical utility and ethical soundness of AI-driven systems for the diagnosis of eye diseases.

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