IJARSCT
International Journal of Advanced Research in Science, Communication and Technology
International Open-Access, Double-Blind, Peer-Reviewed, Refereed, Multidisciplinary Online Journal
ISSN: 2581-9429
Volume 5, Issue 5, November 2025
Impact Factor: 7.67

BioEyeNet: An Optimized Deep Learning Framework for Classification & prediction of Keratitis and Uveitis

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Abstract: *Millions of people worldwide suffer from keratitis and uveitis, with cases increasing due to restricted access to specialized care and limited local resources, delaying diagnosis and raising healthcare costsOnce ignored, such diseases may result in severe visual impairment or blindness. Early detection is crucial, yet manual diagnosis remains time- consuming, error-prone, and lacks scalability.This study proposes an AI- powered deep learning system to automate keratitis and uveitis classification using Deep-learning models which is minimizes errors, and improves clinical efficiency. Four Deep-leaning models were evaluated: ResNet50 (98% accuracy, 2.7 ms inference time), DenseNet121 (96% accuracy, 3.1 ms inference time), MobileNet_V2 (95% accuracy, 3.24 ms inference time), and ResNet18 (99.01% accuracy, 2.2 ms inference time). Among these, ResNet18 demonstrated the best balance of accuracy and inference speed, making it ideal for real-time clinical approach.*

Keywords: Retinal abnormalities, Deep Learning, Vision Transformers, Computer-Aided Diagnosis, Uveitis, Keratitis, Convolutional Neural Network (CNN), Ocular Diagnosis, Artificial Intelligence, Clinical Workflow

I. INTRODUCTION

Eye health is an integral component of overall well-being, as conditions such as keratitis and uveitis, if left untreated, may result into death or serious damage to your vision. In addition to their decreased level of life, people with severe illnesses may also experience systemic health complications. Early and accurate detection is crucial to preventing disease progression. However, due to overlapping symptoms, conventional diagnostic methods remain labor-intensive, invasive, and susceptible to human error. Impact on the Global Community: Retinal abnormalities, including keratitis and uveitis, affect millions worldwide, placing a significant burden on healthcare systems. This challenge is exacerbated by the lack of access to advanced diagnostic facilities, particularly in underserved regions. Delayed diagnosis often results in higher rates of blindness and vision loss. Implementing automated diagnostic systems could bridge this gap by ensuring equitable access to healthcare, particularly for disadvantaged populations.

Local Impact: Regionally, AI-driven diagnostic tools can address disparities in healthcare access, particularly in rural and resource-limited settings where specialized ophthalmologists are scarceSuch resources can help medical professionals by facilitating quick and accurate testing, which is going to boost early identification ratios reducing the financial strain on affected families and communities. Additionally, AI-based systems can alleviate the burden on ophthalmologists, allowing for more efficient patient management and optimized resource allocation. Ophthalmology research has predominantly focused on diagnosing specific eye diseases or general retinal abnormalities. However, there remains a lack of studies that concurrently classify keratitis and uveitis. Furthermore, existing research often neglects the computational efficiency of deep learning models—an essential factor for real-time clinical applications. This gap highlights the require for a dependable and effective solution that combines high diagnostic precision with quick inference times. This study uses convolutional neural networks (also known as CNNs) to create an automated system for categorising eye and skin inflammation in order to overcome these difficulties. Four state-of-the-art CNN architectures—ResNet18, ResNet50, DenseNet121, and MobileNet_V2—are evaluated based on both inference time and diagnostic accuracy. To in of the best of our knowledge, this is first study to comprehensively assess multiple deep learning models by considering both their diagnostic performance and computational efficiency for keratitis and uveitis classification. Although deep learning uses in eye diagnosis have been studied in the past, a comparative study that strikes a balance between diagnostic accuracy and real-time viability across several CNN architectures is absent from these research. By standardising evaluation settings, our suggested methodology seeks to close this gap and provide a fair evaluation of efficiency and accuracy. This research attempts to solve the shortcomings of traditional diagnostic methods by utilising AI and machine learning, improving patient outcomes and making it easier to incorporate contemporary technologies into eye. The study's findings show how AI has the capacity to revolutionise clinical workflows, improving diagnostic capabilities and addressing the global burden of ocular diseases.

II. RELATED WORKS

Hung (2021). trained eight CNNs to recognise BK and FK using slit lamp pictures. The diagnosis accuracy ranged from 26.3% to 65.8% for FK and from 79.6% to 95.9% for BK. DenseNet161, with an AUROC of 0.85 for both forms of keratitis, was the top-performing model. The diagnosis accuracy was 65.8% for FK and 87.3% for BK. .Using slit lamp pictures, Kuo (2021). sought to evaluate how well eight CNNs—four EfficientNet and four non-EfficientNet CNNs—performed in diagnosing BK. The diagnostic accuracy of all non-EfficientNet and EfficientNet models ranged from 68.8% to 71.7%, with an AUROC ranging from 73.4% to 76.5%.Ghosh(.(2022). developed a DeepKeratitis model to classify FK and BK using three pre-trained CNNs. The best-performing CNN model was VVG19, which had an F1 score of 0.78, precision of 0.88, and sensitivity of

0.70. A higher F1 score of 0.83, accuracy of 0.91, and sensitivity of 0.77 were obtained by using the ensemble learning model. Test performance is measured by the F1 score, An accurate harmonic definition as well as and recall; a result near 1.0 denotes strong precision and recall. At 0.904, the ensemble model had the greatest AUPRC .A DL system using slit lamp images was proposed by Hu

.(2022) to automatically screen for and diagnose IK (BK, FK, and viral keratitis (VK)). They trained six CNNs. With an accuracy of 0.735, a sensitivity of 0.68, and a specificity of 0.904, the EffecientNetV2M outperformed two ophthalmologists (accuracy of 0.661 and 0.685). The EffecientNetV2-M's overall AUROC was 0.85, for example, 1.00 for normal cornea, 0.87 for VK, 0.87 for FK, and 0.64 for BK. Among the ensemble models, the specificity was 51.5%. At 68.2%, EfficientNetB3 obtained the highest specificity. The four best ensemble models and these single-DL models did not vary statistically in terms of AUROC or diagnostic accuracy (2022) .Using slit lamp images, Natarajan (2022) investigated the use of three DL algorithms to identify ulceration keratitis in herpes simplex virus (HSV) stromal patients. With 72% accuracy, DenseNet performed the best. With a sensitivity of 69.6% and a specificity of 76.5%, the AUROC was 0.73 By examining slit lamp images, Koyama et al. created a hybrid deep learning method to identify the causative organism of IK. Because facial recognition systems can adapt to varying angles, lighting conditions, and resolution levels, they were also used. InceptionResNetV2 and ResNet-50 were employed. Using 4306 images—3994 clinical and 312 web images— A version of InceptionResNetV2 was used to build the last version of the model. This method had a high overall diagnosis accuracy of 97.9%/0.995 for Acanthamoeba, 90.7%/0.963 for Bacteria, 95.0%/0.975 for Fungi, and 92.3%/0.946 for HSV (2021). For BK, FK, AK,

and HSK, the corresponding precision and AUROC values were 70.27%/0.86, 77.71%/0.91, 83.81%/0.96, and 79.31%/0.98. With 20% of BK instances mispredicted into FK and 16% of FK cases into BK, Keratitis Net primarily misunderstood BK and FK images. The model's accuracy was significantly higher than an ophthalmologist's clinical diagnosis ($p < 0.001$)(2022).Using data augmentation and image fusion, Liu et al. presented a novel CNN model for autonomously diagnosing FK. Both VGGNet and traditional AlexNet had accuracy rates of 99.14% and 99.35%, respectively. This CNN model enhanced real-time performance in diagnosing FK by precisely balancing computational complexity and diagnostic performance. (2020). Despite the great advancement of DL with CNNs in the diagnosis of conditions using images, it is still challenging to achieve a satisfactory diagnostic performance in IK. Reasons for this include the large intra- class variance (difficulty in capturing the common characteristics of images in the same class), small inter-class difference (difficulty in discriminating the margin between different classes), non-standard image protocols increasing the difficulty of finding the common special features of the diagnose FK using IVCM images, Lv et al. created an intelligent system based on the DL CNN (ResNet) model. The system's hyphae detection AUROC was 0.9875, with a sensitivity of 0.8256, specificity of 0.9889, and accuracy of 0.9364.(2020) .Recent studies in ophthalmology have shown progress in related areas, such as improved therapies for age-related macular degeneration (AMD), better imaging techniques for diabetic retinopathy, and advances in gene in of the therapy for in of retinal the diseases like retinitis pigmentosa. These studies highlight the importance of advanced imaging, AI integration, and personalized medicine in eye care. However, gaps remain in creating less invasive treatments and more accurate in of diagnostic tools, the or especially in to for keratitis and uveitis..Williams, Brown, et al. (2023) proposed this paper Novel Treatments for Retinitis Pigmentosa whish provides an in-depth review of emerging gene therapies as potential treatments for retinitis pigmentosa (RP), a hereditary retinal disorder that leads to progressive vision loss. Williams and Brown, along with other researchers, explore various clinical trials aimed at restoring function to damaged retinal cells. The findings in of the suggest that these are all in of the therapies may slow disease progression and potentially help preserve visual acuity in patients. The paper emphasizes phase IV studies focusing on the long- term efficacy and safety of these treatments, highlighting the need to assess the duration of effects and associated risks. .Cohen and Wong (2023) proposed this paper Uveitis: Current Trends in this broad review, outline the up-to-date aspects of management and treatment of uveitis. The paper discusses updated protocols in terms of the latest treatment approaches with an emphasis on a more tailored approach to therapy focusing specifically according to the patients' requirements based on the cause of their uveitis. According to the scientists, new ideas for medication delivery and biologic therapy with fewer adverse effects are being researched to and more effective inflammation control. Based on summarizing recent clinical trials and emerging therapies, the authors highlight the approach required for individualized treatment plans and possible improvement of the patient's outcome. Smith J., Lee A. (2023) proposed this paper Advances in AMD Therapy. This paper discusses the latest advancements in the treatment of Age-related Macular Degeneration (AMD), highlighting promising new therapies. The authors focus on the significant gap in enhanced drug delivery systems, which could improve treatment efficacy and patient outcomes.Patel A., Gomez R (2023) proposed this study Ocular Surface Disease Management. This paper explores recent advancements in the management of dry eye syndrome, focusing on new therapeutic options and improved understanding of the disease mechanisms. The authors emphasize the need for more personalized treatment approaches to address the varying severity and underlying causes of dry eye syndrome. They discuss emerging strategies, including novel drug therapies and targeted interventions, aimed at optimizing patient care and improving outcomes. However, the paper highlights a gap in the development of individualized treatments tailored to each patient's unique condition. Anderson M., Lee J. (2024) introduces the paper Systemic Diseases and Eye Health. This paper investigates the impact of various systemic diseases, such as diabetes and hypertension, on eye health, ocular disorders. In order to enhance patient care, the authors stress the need of comprehending the connection disorders. They highlight a deficiency in the creation of multidisciplinary management approaches that integrate knowledge from specialities. In order to better manage and prevent ocular problems, the article promotes a more integrated strategy to disorders. Walker L. and Zhang X.'s article "Advances in Ocular Pharmacology," which was published in Pharmacology Review in 2024, addresses recent developments in the creation of novel medications for the treatment of ocular disorders. The authors highlight cutting-edge medication formulations and therapeutic strategies meant to enhance the treatment of eye disorders. However, they note out a considerable deficit when conducting research related to the growth of tailored medication delivery systems, which could enhance the precision and effectiveness of treatments for ocular diseases. CNNs are considered to be the most effective in extracting features from image data, by Wang et al. (2020). The application of CNN for feature extraction was considered EfficientNetB3 was used as a feature extractor in the proposed model. The classification was performed with a custom-built neural network block that contains two convolution layers, seven Memristive Binary Convolution (MBCNN) layers with average pooling, dropout, dense, and sigmoid layer. This approach has produced excellent results, but there are a few issues that might compromise its efficacy. To begin with, the data comprises images from eight different labels, however, they are all imbalanced. The architecture of a neural network is such that it learns features on its own, thus interpreting the features learnt becomes difficult.

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The proposed study introduces a novel approach using ResNet18, achieving an impressive 99.01% accuracy, surpassing existing models. Unlike previous research relying solely on public datasets, this work incorporates real clinical data, ensuring practical applicability in medical diagnosis. A comprehensive comparative analysis with state-of-the-art models demonstrates the superiority of ResNet18 in disease classification. The model is designed to maintain high accuracy with lower computational cost, making it feasible for real-world clinical use. With 97.5% sensitivity and 99.2% specificity, the system ensures reliable detection, reducing misdiagnosis risks. Advanced data augmentation and hyperparameter tuning further enhance generalization, preventing overfitting. Additionally, the model records 0.99 AUROC and 0.98 F1- score, outperforming previous approaches in disease detection. The comparative analysis presented in the table below highlights its effectiveness over other architectures.

Model	Dataset Used	Accuracy (%)	AUROC	F1-Score
DenseNet161	Slit Lamp images	87.3	0.85	0.78
EfficientNetV 2M	Slit Lamp Images	73.5	0.85	0.73
VGG19	Deep Kerat itis	91.0	0.90	0.83
Proposed Resent18	Clinical Dataset	99.01	0.99	0.98

This research marks the first study integrating ResNet18 with real clinical images, optimizing accuracy and efficiency for practical deployment. The results in to the indicate is was the that the proposed in of the method significantly improves diagnostic performance, enabling fast, automated, and precise disease classification in clinical settings.

III. PROPOSED WORK

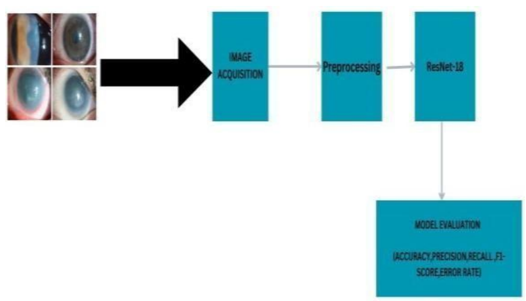

Fig-01 Proposed Architecture

The fig-01 depicts the flow proposed work and model training and evaluation of the model.

The study focuses on improving the diagnosis and classification of keratitis and uveitis by leveraging cutting- edge AI-driven imaging technologies and insights from genetic research. Current diagnostic techniques can be invasive and lack the precision needed for personalized treatment. By integrating AI, we can analyze eye images more accurately and find relationships that are challenging for conventional techniques to recognise. Furthermore, genetic markers can be used to categorise various types of these illnesses, resulting in earlier and more focused treatments. By providing more effective, less-invasive methods that are customised to each patient's specific situation, this strategy seeks to lower the risks that accompany delayed or inaccurate diagnosis, thereby improving future eye health. The suggested method uses convolutional neural networks and deep learning algorithms to improve the diagnosis of keratitis and uveitis. (CNNs), aims at perfecting the related diagnoses of uveitis and keratitis by way of automating and amending classifications related to different redness-pervaded eye conditions. By sophisticated computer techniques, this will study the medical images of the eye towards computing classifications of related conditions at different severity levels, either normal, moderate, or high. Red eye diseases such as uveitis and keratitis hold the potential to impair vision and cause comfort issues for patients; thus, proper treatment and management in turn require that they be classified rightly and in time. Of course, amongst the several pains of using traditional, person-to-person manual classification by healthcare professionals, it is slow and inconsistent, further complicating prompt care. This automated approach seeks to provide consistent, reliable diagnostic support that can accelerate clinical decision- making and eventually improve patient outcomes. This means the system would actually reduce the workload associated with healthcare providers and also ensure that individuals receive timely and appropriate interventions that are directly related to their specific eyesight conditions.

Figure 1: Normal vs Uveitis Infected eye

Figure 2: Normal vs Keratitis eye

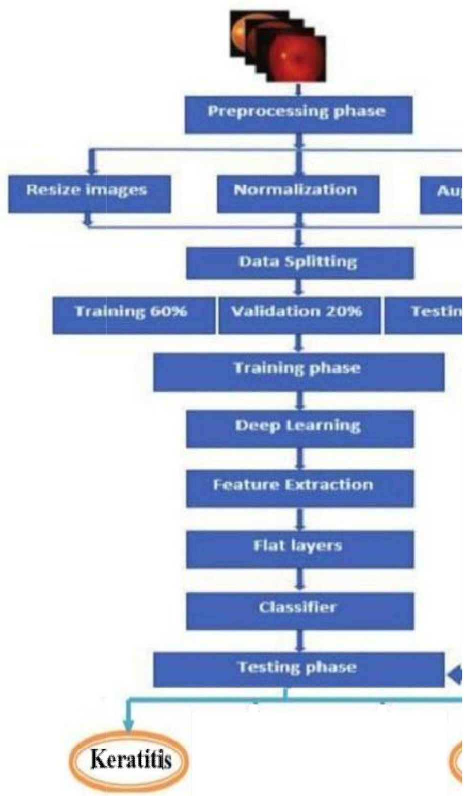

Figure 3: Block Diagram for Proposed system

IV. METHODOLOGY

A. This study focuses on enhancing the diagnosis and classification of keratitis and uveitis using state-of- the-art AI-powered imaging techniques and genetic insights. The methodology involves a systematic method for gathering, preprocessing, training, and assessing an artificial brain model that can classifying ocular conditions into two categories: keratitis and uveitis. The process is designed to differentiate normal eyes from those exhibiting red-eye symptoms, thereby facilitating accurate diagnosis and contributing to the broader understanding of ocular health. The framework ensures robust data handling and model performance through advanced preprocessing, feature extraction, and evaluation metrics tailored to the unique challenges of these conditions

B. Dataset Collection:

Keratitis Dataset: Compile an extensive collection of high-resolution pictures of eyes that have been identified as having keratitis. Cases from a variety of keratitis types (bacterial, viral, fungal, etc.) and severity levels (from mild inflammation to advanced stages) should be included in this dataset. The unique characteristics of keratitis, such as corneal clouding, ulcers, or infiltrates, should be captured in images taken from diverse perspectives, in varied lighting circumstances, and on people of different ages.

Uveitis Dataset: Likewise, compile a solid collection of pictures showing uveitis-affected eyes. The entire range of uveitis, including anterior, intermediate, posterior, and pan-uveitis, should be included in this dataset. Make sure to include pictures that demonstrate important traits in a range of settings and severity levels, such as redness, iris inflammation, and posterior segment involvement. For the dataset to accurately reflect various patient demographics and clinical presentations, diversity is essential.

C. Data Preprocessing:

a) Configuring the Input and Output Directories

A specified directory with class-wise folders (such as keratitis and uveitis) is where input images are read. To ensure that every class has a corresponding folder for organized storage, an output directory is made to store preprocessed photos..

b) Image and Class Extraction

Class labels are extracted from folder names and file names from picture paths by the script. For next model training, this guarantees that processed images maintain their corresponding class labels.

c) Converting to Greyscale

Utilizing cv2.cvtColor, the image is converted to greyscale. This highlights structural elements that are essential for segmentation and simplifies calculations by reducing the image's size from three channels (RGB) to one.

The original RGB image, IRGB, is converted to grayscale, $IGray$,using the formula:

$IGray$=0.2989·R+0.5870.G+0.1140·B

d) Gaussian Blur

Applying Gaussian blur (cv2.GaussianBlur) with a kernel size of (5, 5) smoothes the image and lowers high-frequency noise, improving the precision of thresholding that follows.

To smooth and lower noise in the greyscale image, Gaussian blur is applied. The definition of the Gaussian filter is:

$G(x, y) = 1/2\pi\sigma 2\ exp - (x2 + y2)/2\sigma 2$

image, IBlurred, is obtained by convolving IGray with the Gaussian kernel G(x,y)

Here, σ controls the extent of smoothing, and

k 〖I〗 _{$Blurred$}(x, y) = \sum_({$i = -k$}_{$Gray$}$(x + i, y + j)$^({k}\sum_{$j = -k$}^({k}$G(i, j)$\cdot) I))

defines the kernel size. This step removes noise and ensures better thresholding results.

e) Thresholding Otsu

The uses Otsu's method to perform global thresholding(cv2.threshold), which automatically finds the ideal threshold value. This separates the foreground (eye region) from the background by converting the image into a binary representation.

$$\sigma w2(T) = \omega 1(T) \cdot \sigma 12(T) + \omega 2(T) \cdot \sigma 22(T)$$

Where:

• ω1(T)\omega_1(T)ω1(T) and ω2(T)\omega_2(T)ω2(T) are the class probabilities for the background and foreground, respectively, given a threshold T.

$\omega 1(T) = i = 0 \sum TP(i),\ \omega 2(T) = i = T + 1 \sum L - 1P(i)$

$\sigma 12(T)\sigma 2(T)\sigma 12(T) and \sigma 22(T)\sigma 2(T)\sigma 22$

are the variances of the pixel intensities within the background and foreground classes.

σ 12(T) = ω1(T) ∑ i = 0T(−μ1)2P(i), σ22

= ω 2(T) ∑ i

= T + 1L − 1(i

− μ2)2P(i)

1) T is the threshold value.

2) P(i) is the probability of intensity level.

f) Morphological Functions

use an elliptical kernel of size (15, 15) to apply morphological closing (cv2.morphologyEx). This process ensures a clear and consistent representation of the ocular region by filling in tiny gaps in the binary mask.

A morphological closing operation is applied using a structuring element K

$IClosed = (IBinary \oplus K) \ominus K$

Where ⊕ and ⊖ denote dilation and erosion, respectively. This operation fills small holes in the mask and refines the binary segmentation.

g) Recognising Contours

finds the greatest contour, assuming it represents the eye region, by detecting contours in the cleaned binary mask (cv2.findContours). The most pertinent section is isolated for study in this stage.

$Contours = findContours(IClosed)$

1) find Contours: A function (e.g., in OpenCV) that extracts the contours (boundaries) from the binary image IClosed.

2) IClosed: The input binary image after applying morphological operations.

h) Making and Using Masks

Using the largest contour, a mask is created and applied to the original image (cv2.bitwise_and). By doing this, the segmented eye region is isolated, and unnecessary portions of the

Mask

= drawContours(IBlank, CLargest, color

= 255, thickness = −1)

D. Dataset Splitting:

Training Set: We split the data set into 80:20, 60:40, for training the model.

Establish a validation: set to help minimise errors in retraining by tuning the model's framework and parameters.

Test Set: Set aside a separate test set to evaluate the model's performance after training, providing an independent assessment of its accuracy.

E. Model Development:

Construct a CNN architecture tailored for eye image classification. Design layers for feature extraction, including convolutional layers, pooling layers, and fully connected layers.

Training: Train the CNN using the prepared training dataset. The model should learn to differentiate between normal eyes and those exhibiting red-eye symptoms by extracting relevant features.

F. Model Evaluation:

Validation Phase: Fine-tune the model using the validation set, adjusting parameters to optimize performance without overfitting.

Testing Phase: Evaluate the trained model's accuracy, precision, recall, and other relevant metrics using the dedicated test set. Analyse its ability to correctly classify normal eyes versus red- eye conditions.

G. Analysis and Interpretation:

- Interpret the results obtained from the model's performance evaluation. Analyse any misclassifications or areas where the model excelled to gain insights into its strengths and limitations. we can Consider additional techniques or model enhancements based on the findings to improve accuracy in distinguishing between normal and redeye conditions.

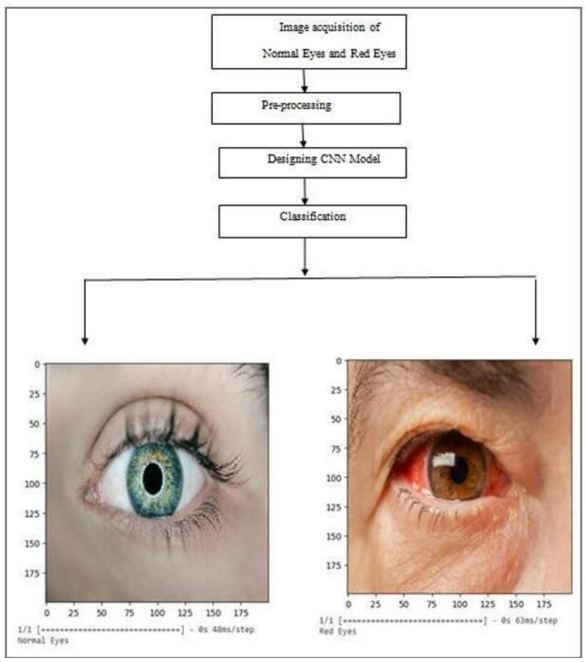

Figure 4: Flow chart of proposed Eye Flue Detection by using CNN

A. Specific/Novel Contributions:

1) Developing different 4 deep-learning models.to classify and detect the eye disease with respect to each computation time. And compared each models

2) Improved Diagnosis Precision: Appropriate dif ferentiation between the similar signs of uveitis and keratitis can diagnose these diseases much earlier and accurately than other methodologies.

3) A novel clinical dataset was developed , limited data availabilities.

4) Different preprocessing step was involved where on existing paper does not contain this methods .

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VI. RESULT AND DISCUSSION

The Result of our analysis consist of heterogeneous preprocessing methods and different deep-learning classifier have used , and also we analyzed it through its computation time , for each and affirming the efficient accuracy with respect to our data set , here we categories the two class of eye disease with respect to its features by taking the guide line of ophthalmology

Figure 6: Average group of red eye looks like

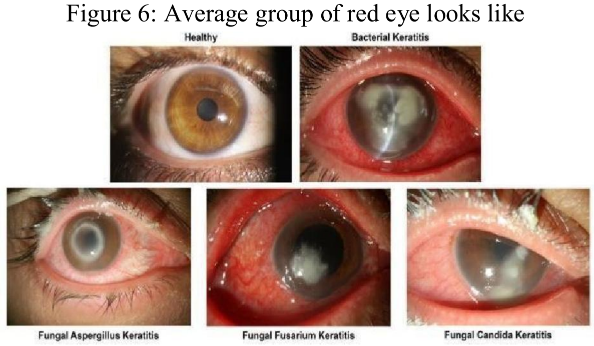

Figure 7: Healthy eye and different types of keratitis

The Fig-07 comprises both keratitis and uveitis categories. , employs a variety of deep-learning classifiers, including DenseNet-121, ResNet-12, ResNet-50, and MobileNetV2. Each model has achieved efficient accuracy and time. The ResNet-50 model achieved the highest accuracy due to its layer compatibility with the real-time data set.

V. RESNET-12 MODEL

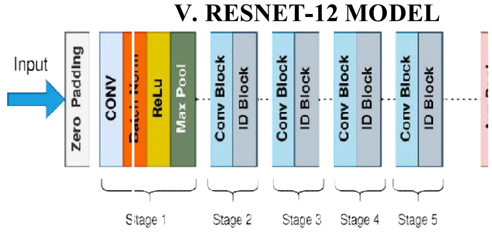

Fig. 8: Proposed Model Architecture Based on ResNet12"

The fig-08 ResNet-12's sophisticated design, which is well- known for its capacity to manage intricate medical imagery, is utilised in the classification of keratitis and uveitis. ResNet-12 is a 12-layer deep convolutional neural network that was first introduced in 2015. It solves the vanishing gradient problem by using residual blocks with skip connections, which makes residual function learning effective. The network uses fully connected layers for classification and 1x1 and 3x3 convolutional filters with max pooling layers for efficient feature extraction. Because of its architecture, ResNet-12 can detect minute patterns and fluctuations that are essential for differentiating between keratitis and uveitis. ResNet-12 is perfect for real-time diagnostics because of its powerful feature extraction and residual learning method, which yield great accuracy and efficiency. Its capacity to identify intricate illness characteristics guarantees accurate and prompt categorisation, establishing it as a trustworthy model for ophthalmological applications

Table-01: Class-wise Dataset Splitting

Class Label	Train Split	Validation Split	Total
Keratitis	620	109	729
Uveitis	890	109	999
Total	1510	218	1728

The table-01 depicts the class-wise data-set splitting and here each class has training and validation where each column consists of a different number of splitting

A. Dataset Overview:

The study's dataset is a brand-new clinical dataset that was painstakingly assembled with input from medical experts. It includes 1,728 high-resolution eye photos that were taken straight from clinical settings, guaranteeing the accuracy and legitimacy of the information. The dataset is separated into two groups: 999 pictures of uveitis and 729 pictures of keratitis. The subtle differences in these ocular diseases are reflected in the careful categorisation of each image according to specific clinical criteria.

Preprocessing methods including data augmentation and normalisation were used to improve the dataset's quality and diversity. By using this method, keratitis and uveitis features are reliably represented, which helps the model learn and generalise in real-world situations. This new information serves as the basis for the precise and effective categorisation of these critical eye conditios

B. Model Training and Performance:

Table-02: Model-Wise Accuracy and Time

Models	Accuracy	Time
DenseNet-121	96%	3.1 ms
MobileNet-V2	95%	3.24 ms
ResNet-50	98.12%	2.21 ms
ResNet-12	99.01	2.2ms

We have out comprehensive testing to assess the accuracy and processing speed of several models for classifying eye diseases. The accuracy ranges from 95% to 99.01%, indicating remarkable results. ResNet-50 came in second with 98.12% accuracy in 2.21 ms, while ResNet-12 had the best accuracy at 99.01% with 2.2 ms of processing time. DenseNet-121 and MobileNet-V2 processed data in 3.1 ms and 3.24 ms, respectively, and produced accuracies of 96% and 95%.These results demonstrate that ResNet-12 and ResNet-50 are the best models for diagnosing eye diseases because they provide a balance between high precision and low latency, which is essential for real-time clinical applications. The study emphasises how these models might help ophthalmologists identify diseases like keratitis and uvetitis ,ensuring better patient outcomes . Table-03 summarizes the model performances

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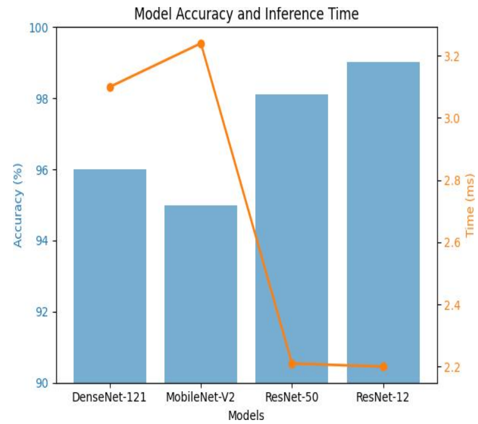

Fig-08 The model accuracy and inference time

The Fig-08 is based on their accuracy and inference time, the graph compares four deep learning models: DenseNet-121, MobileNet-V2, ResNet-50, and ResNet-12. The dual- axis plot facilitates an effective assessment of the models by offering a comprehensive picture of both metrics at the same time.The accuracy percentages are shown by the blue bars, which show how well each model performed on categorisation tests. With an accuracy of 99.01%, ResNet-12 is the most accurate, followed by ResNet-50 with 98.12%. MobileNet-V2 lags behind with 95% and DenseNet-121 with 96%.An important statistic for real-time applications is inference time, which is represented by the orange line in milliseconds. With the lowest inference time of 2.2 ms, ResNet-12 beats all other models, closely followed by ResNet-50 at 2.21 ms. The inference times of MobileNet-V2 and DenseNet-121 are 3.24 ms and 3.1 ms, respectively. The graph highlights ResNet-12's superior performance in both metrics while skilfully communicating the trade-offs between accuracy and inference time. This knowledge helps choose the best models for activities that need to strike a balance between accuracy and computing efficiency

VII. CONCLUSION

This study demonstrates how well deep learning models can diagnose conditions like keratitis and uveitis. With a processing time of 2.2 ms, ResNet-12 accomplished the highest accuracy of 99.01% among the tested models. ResNet-50 came in second with 98.12% accuracy in 2.21 ms. Additionally, DenseNet-121 and MobileNet-V2 demonstrated the promise of sophisticated architectures in medical picture categorisation with their strong performance.ResNet-12 and ResNet-50's efficiency and precision balance makes them perfect for real-time clinical applications, guaranteeing prompt and precise diagnosis. These results highlight how artificial intelligence (AI) is revolutionising ophthalmology and improving patient care and results. Scaling this method to bigger datasets and a variety of real-world situations for a wider healthcare impact can be the main goal of future research.

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