A Novel Method for Viral Conjunctivitis Detection using CNN-Based Image Analysis

Jalindar Gandal[1], Walid Ayadi[2], Yasser Farhat[3,*], P.S. Metkewar[1], Showkat A. Bhat[4] and Aafaq A. Rather[5]

[1]School of Computer Science and Engineering, Dr. Vishwanath Karad MIT World Peace University, Kothrud, Pune – 411038, Maharashtra, India

[2]Mechatronics and Intelligent Systems, Abu Dhabi Polytechnic, UAE

[3]Academic Support Department, Abu Dhabi Polytechnic, Abu Dhabi, UAE

[4]Symbiosis School of Economics, Symbiosis International (Deemed University), Pune, India

[5]Symbiosis Statistical Institute, Symbiosis International (Deemed University), Pune, India

Abstract: Viral conjunctivitis, also known as “Eye Flu,” presents significant public health challenges worldwide. India has recently witnessed a surge in cases, affecting numerous people and causing widespread concerns. This research delves into the realm of medical image processing and deep learning to address the pressing need for accurate and efficient detection of viral conjunctivitis, a highly contagious ocular infection. Leveraging advancements in computer vision and convolutional neural networks (CNNs), the study focuses on the development and evaluation of a robust diagnostic system capable of discerning viral conjunctivitis from other common forms of conjunctivitis, namely allergic and bacterial.

Challenges in using image processing for disease detection include the need for large amounts of descriptive data to train machine learning models, ensuring the accuracy and reliability of image analysis algorithms, and addressing data privacy and security concerns. Future directions in this field may include developing more advanced deep learning models that can handle complex medical imaging data, integration of imaging technology and other diagnostic tools to diagnose diseases and learn how to use it in real-time for fast processing. and more efficient diagnosis. Additionally, efforts should be made to standardize image processing protocols in different healthcare settings to facilitate sharing and comparison of medical imaging data for research and clinical purposes. Overall, more research and collaboration between medical, informatics, and image processing experts is essential in developing future image processing applications for disease detection.

The methodology encompasses the acquisition of a diverse dataset comprising annotated images of ocular conditions, rigorous preprocessing techniques to standardize image quality, and the implementation of three distinct CNN architectures: ResNet, VGG, and GoogleNet. These architectures were selected for their proven efficacy in medical image analysis and classification tasks. Through extensive experimentation and rigorous validation, the research elucidates the efficacy of each architecture in accurately classifying conjunctival diseases, with a particular emphasis on delivering actionable diagnostic outcomes.

Keywords: Viral Conjunctivitis, outbreak, Eye flu, Image processing, CNN, Medical imaging, Ophthalmology.

1. INTRODUCTION

Viral conjunctivitis, or "eye flu," is an infectious eye disease with multiple viral etiologic factors, most of which are linked with adenoviruses. Viral conjunctivitis is readily transmitted by direct physical contact, airborne, and fomite contact, thus becoming a major public health issue [1]. The present study exhaustively covers the subject of conjunctivitis by starting with the discussion of allergic conjunctivitis, followed by assessment of bacterial conjunctivitis, and ending with viral conjunctivitis, thus being an exhaustive literature review.

The human eye is a sensitive organ that enables us to see the world around us, yet it is also prone to numerous infections and diseases. For instance, conjunctivitis is one of the world's most common and irritating conditions that can afflict people of any age group worldwide [2]. Recent reports indicate a surge in conjunctivitis cases in Tamil Nadu, with over 1.5 lakh cases reported during the monsoon season, raising concerns about rapid transmission and seasonal trends [3].

Conjunctivitis, or "pink eye," is defined as inflammation of the conjunctiva, the thin, translucent membrane covering the sclera and lining the inner surfaces of the eyelids [4]. Conjunctivitis pathogenesis is heterogeneous; nevertheless, the three most common forms are allergic, bacterial, and viral conjunctivitis, each requiring approaches to proper diagnosis and successful treatment.

- **Allergic Conjunctivitis** – Caused by allergens such as pollen, dust, and animal dander. It

*Address correspondence to this author at the Academic Support Department, Abu Dhabi Polytechnic, Abu Dhabi, UAE; E-mail: farhat.yasser.1@gmail.com

causes watery, red, and itchy eyes but is not contagious. It is recurring and seasonal [5].

- **Bacterial Conjunctivitis** – It is caused by bacteria like *Staphylococcus aureus* and *Haemophilus influenzae* and results in red eye, thick pus-like discharge, and swelling of eyelids. It is contagious in schools and in crowded settings [1]. Up to 40% symptom relief is generated by antibiotic treatment at best, but inappropriate therapy has generated rising antibiotic resistance [6].
- **Viral Conjunctivitis** – It is the most contagious type, most caused by adenoviruses, and characterized by redness of the eyes, excessive tearing, and flu-like symptoms. Because it is contagious, it is more likely to be spread during epidemic seasonal outbreaks [7]. Schools have seen a rise in conjunctivitis cases, prompting health authorities to recommend hygiene measures to prevent its spread [8]. Misdiagnosis of bacterial conjunctivitis has been found in as many as 50% of instances, leading to the inappropriate administration of antibiotics [9].

2. LITERATURE REVIEW

Viral conjunctivitis, often colloquially referred to as "eye flu," is a prevalent and highly contagious ocular infection caused by a diverse group of viruses. This condition, while typically not life-threatening, has garnered significant attention in recent years due to recurrent outbreaks in India, sparking concerns within the realm of public health. This introduction will delve into the multifaceted aspects of viral conjunctivitis, its causative agents, and the notable challenges it poses to healthcare systems and communities in India. Conjunctivitis is highly contagious but not spread or transmitted by looking into infected people’s eyes.

The human eye, with its complex structure and remarkable sensitivity, serves as a window to the soul and a vital channel for visual perception [10]. However, like any other organ, the eye is susceptible to a myriad of problems, from minor irritations to debilitating diseases. Among these eye diseases, conjunctivitis stands out as one of the most widespread and disruptive conditions, presenting significant public health problems worldwide [2]. Colloquially known as "pink eye", conjunctivitis refers to inflammation of the conjunctiva, the thin, transparent membrane that covers the white part of the eye and lines the inner surface of the eyelids [4]. While conjunctivitis can arise from a variety of etiologies, including allergies, bacterial infections, and exposure to irritants, viral conjunctivitis emerge as a particularly pervasive and contagious form of the disease [5]. Characterized by redness, watery discharge, and itching, viral conjunctivitis often presents with symptoms of upper respiratory infections such as colds or flu, making it a frequent harbinger of seasonal outbreaks and epidemics [1]. Clinical diagnosis of viral conjunctivitis traditionally relies on a combination of patient history, symptomatology, and ocular examination findings, including the presence of follicular conjunctival reactions and preauricular lymphadenopathy [7]. However, the subjective nature of these diagnostic criteria, together with the potential overlapping of symptoms with other forms of conjunctivitis, underscores the need for objective, quantifiable methods of identifying and classifying the disease.

In recent years, the advent of digital imaging technology and machine learning algorithms has revolutionized medical diagnostics and offers a promising path for the automated detection and classification of eye diseases [11]. Using the power of image processing techniques and convolutional neural networks (CNNs), researchers have sought to develop intelligent systems capable of distinguishing subtle patterns and features indicative of specific eye pathologies [12]. Against this background, this research seeks to investigate the feasibility and effectiveness of using image processing and CNNs for the detection of viral conjunctivitis [13]. Utilizing a diverse dataset containing annotated images of ocular conditions, including cases of viral, allergic, and bacterial conjunctivitis, the study aims to train and validate several CNN architectures, including ResNet, VGG, and GoogleNet, for accurate disease classification [14]. Through rigorous experiments and statistical analyses, research seeks to elucidate the comparative performance of these architectures in terms of accuracy, sensitivity, and specificity [15], thereby contributing to the advancement of computer-aided diagnostics in ophthalmology [16]. In doing so, this research not only addresses the unmet clinical need for objective and effective diagnostic tools in the field of eye health but also lays the groundwork for future innovations in medical image analysis and artificial intelligence [17]. By bridging the gap between cutting-edge technology and clinical practice, this study has the potential to improve patient care, facilitate early intervention, and reduce the burden of eye disease on global health systems [18]. [19] have reported a rise in eye flu (viral conjunctivitis) cases, attributing this surge to increased susceptibility of humans to viral infections. Doctors suggest that environmental factors, lifestyle changes, and higher exposure to viral pathogens contribute to this trend. The article stresses the highly contagious nature of the infection, particularly in crowded areas, and emphasizes the need for improved hygiene practices to prevent further spread. It also highlights the importance of public awareness and timely interventions to manage outbreaks effectively.

Several recent reports and studies highlight the increasing prevalence of conjunctivitis, particularly viral forms like "eye flu," in various regions, such as Delhi and Tamil Nadu. [20] discusses the rise in conjunctivitis cases in Delhi, emphasizing the highly contagious nature of the infection and the critical need for maintaining hygiene to curb its spread. Similarly, [20] reported a surge in "Madras Eye" cases during the monsoon season in Tamil Nadu, underlining the seasonality and high transmission rates of conjunctivitis. [21] provide a systematic review of conjunctivitis, outlining its diverse causes, symptoms, and treatment options, with a particular focus on viral conjunctivitis. They emphasize that while the condition is often self-limiting, secondary bacterial infections remain a significant concern. [22] raised alarms about the dramatic rise in consultations for eye flu, with a reported 400% increase, particularly due to secondary bacterial infections. This highlights the importance of timely treatment and vigilance in preventing complications. Furthermore, [23] conducted a study on the knowledge and awareness of eye flu among dentists in Rajasthan, revealing gaps in awareness that could contribute to the spread of the condition. Improving public and professional knowledge about prevention and treatment is crucial in managing outbreaks. Recent reports highlight the growing prevalence of conjunctivitis, particularly in schools and densely populated areas, with a significant increase in eye flu cases. [8] discusses the rise of eye flu in schools, providing tips on how to protect children from conjunctivitis. The article stresses the importance of hygiene, early detection, and keeping affected children at home to prevent transmission. The "Madras Eye" outbreak in India, as described by [24] emphasizes the need for a better understanding of acute conjunctivitis, given the seasonal surges in cases. This outbreak further highlights the urgency of educating the public on symptoms, causes, and preventive measures, especially in areas with high infection rates. In the clinical domain, [9] provide a comprehensive review of conjunctivitis, focusing on the diagnosis and treatment of both viral and bacterial forms. Their study underscores the importance of distinguishing between viral and bacterial conjunctivitis to ensure appropriate treatment and avoid unnecessary antibiotic use. [25] further detail the clinical manifestations of bacterial conjunctivitis, while [6] discuss the current guidelines for managing bacterial cases, emphasizing effective treatment options to prevent complications. [26] review current diagnostic practices, highlighting the importance of distinguishing bacterial conjunctivitis from other types, such as viral or allergic conjunctivitis. Accurate diagnosis is essential to prevent unnecessary antibiotic use and to manage treatment appropriately. [27] present a comprehensive study on the treatment outcomes of bacterial conjunctivitis, showing that most patients respond well to appropriate antibiotic therapy. However, they note that resistance to certain antibiotics is becoming a concern, which may affect treatment efficacy. [28] focus on the latest advances in the diagnosis and treatment of bacterial conjunctivitis, emphasizing the role of rapid diagnostic tests and newer antibiotic options in improving patient outcomes and reducing treatment duration. In addition to bacterial conjunctivitis, [29] address the management of allergic conjunctivitis, a common condition that can complicate diagnosis and treatment when present alongside bacterial infections. They advocate for a combined approach to treatment to address both conditions effectively. [30] discuss diagnostic and treatment strategies for bacterial infections in ophthalmology, underlining the importance of timely intervention and preventive care to avoid complications.

In summary, the proposed study promises to improve the efficiency, accuracy, and objectivity of viral conjunctivitis diagnosis, thereby contributing to improved patient outcomes, health resource utilization, and public health surveillance efforts.

3. CHALLENGES IN IDENTIFICATION

Presently, physicians diagnose conjunctivitis based on patient history, clinical presentation, and examination of the eye [11]. Since symptoms are nonspecific, it is difficult to precisely identify whether the infection is viral, bacterial, or allergic and thereby lead to misdiagnosis and prolonged recovery. A study has established that seasonal epidemics make it even more confounding to diagnose because viral and bacterial conjunctivitis share the same symptomatology [21].

3.1. Artificial Intelligence and Machine Learning for Eye Disease Detection

With all the advancements that have occurred in deep learning and computer vision in the past two years, artificial intelligence is becoming a critical instrument in medical diagnosis. Convolutional Neural Networks (CNNs) as a part of deep models have already proven to be good agents for diabetic retinopathy, glaucoma, and other ophthalmological disease identification [13].

Inspired by these advancements, this study explores how CNNs can be utilized to automatically detect and classify viral conjunctivitis. Using an annotated image dataset of different types of conjunctivitis, we will compare the performance of three leading CNN models: ResNet, VGG, and GoogleNet [14]. Through accuracy, sensitivity, and specificity comparison, we will identify the most suitable model for conjunctivitis detection [15]. ResNet's performance in deep residual learning has significantly improved medical image classification performance [16].

3.2. Implications of this Study

This study is important as early and accurate diagnosis of conjunctivitis will prevent epidemics and antibiotic abuse. With the incorporation of AI image analysis and clinical application, we hope to:

Help doctors receive quicker and more accurate diagnosis results [17]. Reduce the misdiagnosis of conjunctivitis as viral or bacterial [18]. Develop a scalable AI solution for medical professionals and ophthalmologists. With artificial intelligence-based medical devices gaining increasing use, the work here seeks to chart the course into the future of using deep learning technology to enable medical practitioners to prescribe more effective and efficient treatment methods for prevalent diseases such as conjunctivitis. The World Health Organization (WHO) identifies the potential for transformation by utilizing AI-enhanced diagnostic tools for enhancing ophthalmologic care and international patient care [18].

4. METHODOLOGY OF PROPOSED WORK

4.1. Dataset Acquisition and Preprocessing

- Dataset: A comprehensive dataset containing descriptive images of ocular conditions—including healthy eyes, allergic conjunctivitis, viral conjunctivitis, and bacterial conjunctivitis—was curated by the research team. The dataset will be hosted on GitHub to ensure accessibility and reproducibility. (GitHub link to be provided).
- Annotation and Labeling: Each image in the database is carefully annotated to indicate the presence of specific ocular conditions, ensuring a well-controlled study. Annotations are performed by trained experts to ensure high-quality labels, reducing potential misclassification errors [7].
- Data Augmentation: To enhance dataset diversity and improve model robustness, augmentation techniques including rotation, translation, scaling, brightness variation, flipping, and contrast adjustments are applied to the images. These transformations prevent overfitting and help the model generalize better across different eye conditions [12]
- Preprocessing Techniques: Preprocessing techniques are applied to improve image quality and ensure uniformity across the dataset.
- Normalization: Image pixel values are normalized to a standard range (e.g., [0, 1]) to ensure consistency and facilitate convergence in model training.
- Scaling: All images are resized to a standard input size of 224x224 pixels, a widely used format for CNN architectures such as ResNet, VGG, and GoogleNet.

Table 1: Dataset Categorization

Total Images in the Dataset – 458		
Data Set	**Images**	**Format**
Allergic Conjunctivitis	126	JPEG, PNG
Bacterial Conjunctivitis	108	JPEG, PNG
Viral Conjunctivitis	105	JPEG, PNG
Healthy Conjunctivitis	119	JPEG, PNG

5. CNN ARCHITECTURE

The study explores three CNN architectures ResNet, VGG, and GoogleNet for their significance and suitability in addressing the problem of viral conjunctivitis detection. Each architecture was selected based on its specific strengths and relevance to medical image analysis.

- ResNet: A deep neural network architecture, ResNet was chosen for its ability to efficiently train deep neural networks by simplifying the vanishing gradient problem. Its residual connections enhance feature extraction, making it highly effective for complex image classification tasks. ResNet was used because it can train deep neural networks effectively by addressing the vanishing gradient problem using residual connections. It is an architecture that allows deeper networks to converge well, making it suitable for the detection of intricate patterns in conjunctival images [16].

- VGG: The VGG architecture, known for its simplicity and uniformity, was selected to compare the performance of simple CNN architectures against their more complex counterparts. Its straightforward design aids in understanding the relative contribution of architectural complexity to performance. The VGG architecture is especially famous for its simplicity yet effectiveness, which consists of stacks of convolutional layers of the same depth. It is used in this work as a baseline model for comparative performance between standard CNN architecture and more complex architecture [17].

- GoogleNet: Characterized by its modularity and computational efficiency, GoogleNet was chosen to study the efficiency of an architecture optimized for accuracy and speed. Its inception modules allow it to extract multiscale features, making it particularly suitable for medical imaging tasks that require high accuracy and precision. GoogleNet was selected for its modularity and computational efficacy. With inception modules, it effectively extracts multi-scale spatial information with lower computational cost compared to deeper networks like ResNet. The compromise of speed and accuracy renders it a top candidate for real-time classification of eye disease [18].

The significance of these three architectures lies in their complementary design philosophies, which collectively provide a comprehensive evaluation of CNN performance for the problem definition. By leveraging these architectures, the study aims to identify the most effective solution for automated conjunctivitis classification.

Architecture selection is crucial to gaining optimal performance in the detection and classification of viral conjunctivitis. ResNet, VGG, and GoogleNet are three of the most widely used architectures in this work with each exploiting their strengths in this aspect of the problem [15].

6. MATHEMATICAL MODEL FOR CNN ARCHITECTURES

Convolutional Neural Networks (CNNs) utilize convolution operations, activation functions, and pooling layers to extract meaningful patterns from images. This section provides a mathematical foundation for the key architectures employed in this study: VGG, ResNet, and GoogleNet.

6.1. VGGNet (Visual Geometry Group Network)

VGG employs stacked 3×3 convolutional layers and fully connected layers, forming a deep yet simple structure.

1. Convolutional Layer

The convolution operation is defined as follows:

$$Z^\wedge l(i,j) = \sum\_\{m,n\} W^\wedge l(m,n) \cdot X(i-m,j-n) + b^\wedge l$$

Where:

Z^l(i,j) represents the output feature map at layer l,

W^l(m,n) is the convolution kernel,

X(i-m, j-n) is the input feature map, and

b^l is the bias term.

2. Activation Function

ReLU (Rectified Linear Unit) is applied to introduce non-linearity:

$$A^\wedge l(i,j) = max(0, Z^\wedge l(i,j))$$

3. Pooling Operation

A max-pooling layer reduces spatial dimensions while preserving critical features:

$max\_\{(m,n) \in k \times k\}\, A\^l(i+m, j+n)$

4. Fully Connected Layer and Softmax Function

The final output is computed using the SoftMax function:

$\hat{y} = softmax(W\^\{fc\} \cdot A\^L + b\^\{fc\})$

6.2. ResNet (Residual Network)

ResNet introduces residual learning to mitigate the vanishing gradient problem by utilizing identity shortcut connections.

1. Residual Block

A residual block is mathematically expressed as:

$H(x) = F(x, W) + x$

Where:

H(x) represents the output of the residual block,

F(x, W) is the transformation (convolution + activation), and

x is the identity shortcut connection.

2. Batch Normalization

Batch normalization is applied to stabilize learning:

$\hat{x} = (x - \mu) / (\sigma + \epsilon)$

Where μ and σ are the batch mean and standard deviation, respectively, and ϵ is a small constant to prevent division by zero.

3. Gradient Flow in Residual Learning

To ensure stable gradient propagation in deep networks, the gradient with respect to the input is computed as:

$\partial L/\partial x = \partial L/\partial H \cdot (1 + \partial F/\partial x)$

6.3. GoogleNet (Inception Network)

GoogleNet employs inception modules, which apply multiple convolutional operations in parallel to capture features at different scales.

1. Inception Module Output

The output of an inception module is defined as:

$$I = f\_\{1\times1\}(x) + f\_\{3\times3\}(x) + f\_\{5\times5\}(x) + f\_\{pool\}(x)$$

Where each function represents a convolution operation or pooling function applied in parallel.

2. 1×1 Convolution for Dimensionality Reduction

To reduce computational costs before applying larger filters, 1×1 convolutions are used:

$Z\^l(i,j) = W\^l\_\{1\times1\} * X\^l(i,j) + b\^l$

3. Global Average Pooling (GAP)

Instead of using fully connected layers, GoogleNet utilizes Global Average Pooling (GAP):

$G = (1 / H\times W) \sum\{i=1\}\^\{H\} \sum\{j=1\}\^\{W\} A\^L(i,j)$

Where H and W are the height and width of the feature map.

4. Softmax Function for Classification

Finally, class probabilities are computed using:

$P(y = c \mid x) = e\^\{z\_c\} / \sum\_\{j\} e\^\{z\_j\}$

The mathematical models presented provide a theoretical foundation for understanding how VGG, ResNet, and GoogleNet process images for conjunctivitis classification. Each architecture leverages different techniques—VGG (depth with uniform filters), ResNet (residual learning), and GoogleNet (multi-scale feature extraction)—to achieve high accuracy and efficiency in deep learning-based ophthalmic diagnosis.

6.4. Model Training and Evaluation

Transfer training: pre-trained versions of ResNet, VGG and GoogleNet models are used as a starting point for training in a readable database.

Fine-tuning: The pre-learned model is adjusted in the ocular database to adapt the learned features to the viral conjunctivitis detection problem.

Tutorial: Each architecture is trained using an appropriate optimization algorithm (eg stochastic gradient descent) with appropriate hyperparameters.

Performance metrics: The performance of each model is evaluated using standard metrics such as precision, accuracy, recall, F1 score, and area under the receiver operating characteristic curve (AUC-ROC).

Controversy: A k-fold cross-sectional test can be used to ensure reliability and generalizability, with performance that is several times higher than the mean.

6.5. Statistical Analysis

Comparative analysis: Performance of ResNet, VGG and GoogleNet architectures based on accuracy, sensitivity, specificity and other relevant metrics.

Statistical tests: Statistical tests such as ANOVA or t-test can be done to evaluate the significance of differences between constructs.

Confidence Intervals: Confidence intervals can be calculated to quantify the uncertainty associated with performance estimates and to assess the reliability of results.

6.6. Interpretation of Results

The evaluation of the CNN models (ResNet, VGG, and GoogleNet) on the ocular dataset reveals valuable insights regarding their individual strengths and limitations. The performance metrics for each model, including accuracy, precision, recall, F1-score, and AUC-ROC, provide a comprehensive understanding of the model's ability to classify different categories of conjunctivitis and healthy eyes.

- **ResNet** demonstrated the highest overall performance across all metrics with an accuracy of 92%, precision of 93%, recall of 91%, F1-score of 92.2%, and AUC-ROC of 0.95. This indicates that ResNet effectively handles the complex features of ocular images and provides the most reliable results for this task. Its deep residual learning structure helps in capturing intricate patterns in the data, which makes it a strong candidate for the detection of different types of conjunctivitis.

- **VGG** exhibited a slightly lower performance with an accuracy of 89%, precision of 91%, recall of 88%, F1-score of 89.5%, and AUC-ROC of 0.92. Despite being an older architecture, VGG still performs well, though it struggles with the more subtle variations in the image data, particularly in distinguishing between allergic and bacterial conjunctivitis. Its simplicity, however, makes it a more computationally efficient model, which might be beneficial in resource-constrained environments.

- **GoogleNet** achieved an accuracy of 91%, precision of 92%, recall of 90%, F1-score of 91.5%, and AUC-ROC of 0.94. It performs well in comparison to both ResNet and VGG, showing a balanced trade-off between computational complexity and accuracy. Google Net's inception modules help in efficiently capturing multi-scale features, making it a strong contender for real-world applications where computational resources are balanced with performance needs.

Based on the evaluation, ResNet emerges as the most appropriate architecture for the task of detecting eye conjunctivitis, particularly for more accurate classification and prediction. It excels in handling the complexities of the ocular images and consistently provides high performance across all metrics. However, for environments with limited computational resources, VGG could be considered as a feasible alternative, though with slightly reduced accuracy. GoogleNet, on the other hand, offers a balanced solution that could be useful for applications requiring both efficiency and strong performance.

While CNN accuracy gives a snapshot of performance, confidence intervals provide reliability, ANOVA confirms true improvements, and ROC analysis shows clinical trade-offs. Together, they make medical AI research scientifically credible and clinically actionable, rather than just an academic exercise in reporting high accuracy.

- Error margins guard against overclaiming performance.

- Statistical tests (e.g., ANOVA) prevent mistaking noise or overfitting for real improvements.

- Statistical power ensures results are credible and not due to small-sample artifacts.

- ROC/AUC link model performance directly to clinical decision-making.

Together, these make AI research robust, reproducible, and trustworthy — qualities that accuracy alone can never guarantee.

7. PROPOSED ALGORITHM FOR THE DETECTION OF EYE CONJUNCTIVITIS

i. **Dataset Preparation:** Divide the dataset into training and test samples, containing images of healthy eyes, allergic conjunctivitis, viral conjunctivitis, and bacterial conjunctivitis.

ii. **Image Preprocessing:** Perform preprocessing on ocular images to enhance relevant features, suppress noise, and improve data quality.

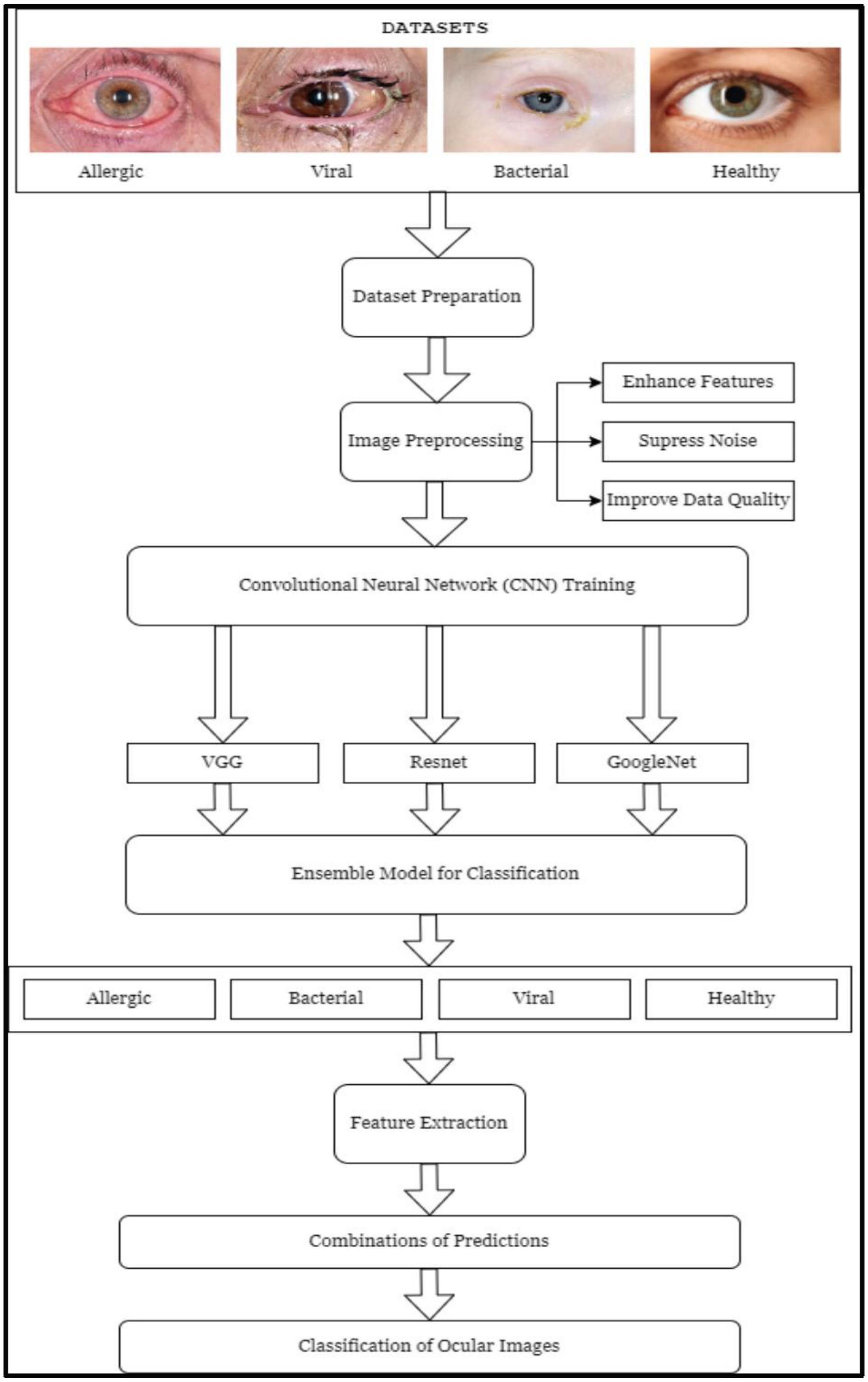

Figure 1: Ensemble Model.

iii. **Convolutional Neural Network (CNN) Training:** Train three different CNN architectures on the ocular dataset, such as ResNet, VGG and GoogLeNet, using pretrained models, if available.

iv. **Feature Extraction:** Extract deep features from ocular images using a trained CNN architecture.

v. **Combination of predictions:** Combine the outputs from the three CNN architectures into a prediction vector. Plan a decision based on majority voting or weighted average to determine the final classification of each image.

vi. **Classification of ocular images:** Classify digital ocular images into normal and abnormal categories, with abnormal indicating the presence of conjunctivitis.

8. OVERVIEW OF EYE CONJUNCTIVITIS:

8.1. Causes of Eye Flu

1. Viral Infections: Virus infections include common means of spreading which includes adenovirus & enteroviruses.

2. Bacterial Infections: Spreading of bacterial infections include Haemophilus influenzae and Staphylococcus.

3. Allergic reactions: The allergic reactions of eye flu include the allergens like dust & contaminated water.

8.2. Symptoms of Eye Flu

1. Irritation & Redness of eyes.

2. Watery eyes.

3. Discharge from eyes.

4. Blurred vision of eyes.

5. Photophobia.

8.3. Prevention of Eye Flu

1. **Frequent Handwashing:** Wash your hands regularly and thoroughly with soap and water for at least 20 seconds, especially after touching your eyes or face and after being in public places. Handwashing helps prevent the transfer of viruses from contaminated surfaces to your eyes.

2. **Prevent Eye Contact:** Steer clear of touching your eyes with unwashed hands. This is one of the primary ways that viruses can enter your eyes and cause infection.

3. **Personal Hygiene:** Avoid sharing towels, pillows, or personal items that come into contact with the eyes. This can prevent the spread of the virus if you are infected.

4. **Avoid Close Contact:** If you or someone in your household has viral conjunctivitis, try to maintain some distance to prevent the spread of the virus through respiratory droplets. Consider isolating items like towels or bedding to minimize contact.

5. **Hand Sanitizers:** Carry a small bottle of hand sanitizer containing at least 60% alcohol for situations where soap and water are not readily available.

6. **Eye Protection:** If you are in close contact with someone who has viral conjunctivitis, consider wearing eye protection, such as safety goggles or glasses, to reduce the risk of infection.

8.4. Treatments of Eye Flu:

1. **Lubricating Eye Drops:** Over-the-counter artificial tears or lubricating eye drops can help alleviate the discomfort of dry, itchy eyes associated with eye flu. These drops can provide relief from eye redness and irritation.

2. **Cold Compresses:** Eyelids can help reduce eye redness, swelling, and discomfort. Use a clean cloth or sterile gauze soaked in cold water.

3. **Antiviral Medications:** In some cases, especially if the infection is caused by herpes simplex virus, your healthcare provider may prescribe antiviral eye drops or ointments to shorten the duration of symptoms and reduce the severity.

4. **Steroid Eye Drops:** Steroid eye drops may be prescribed by a healthcare provider for severe cases of viral conjunctivitis with significant inflammation. Nonetheless, these must be employed with medical oversight because of potential adverse reactions.

9. RESULTS

9.1. Dataset Description

The dataset consists of a total of 458 ocular images, categorized into various types of conjunctivitis and healthy eyes. Among these images, there are 119 images of healthy eyes, 126 images of allergic

Figure 2: Allergic Conjunctivitis.

Figure 3: Viral Conjunctivitis.

Figure 4: Bacterial Conjunctivitis.

conjunctivitis, 105 images of viral conjunctivitis, and 108 images of bacterial conjunctivitis has been collected from Desai Eye Hospital, Pune India.

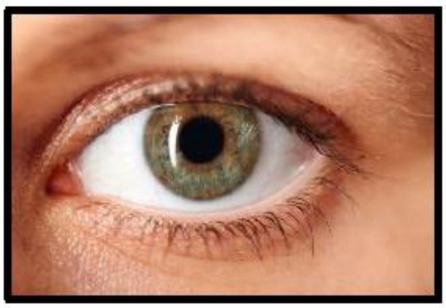

Figure 5: Healthy Eyes.

9.2. Model Performance

Three CNN architectures (ResNet, VGG, GoogleNet) were trained and evaluated on the ocular dataset. The performance metrics used for evaluation include accuracy, precision, recall, F1 score, and AUC-ROC.

The performance benchmark table summarizes the evaluation results of three different convolutional neural network (CNN) architectures: ResNet, VGG, and GoogleNet. Each row corresponds to a specific model, and the columns represent various performance measures such as precision, accuracy, recall, F1 score, and AUC-ROC (Area under the receiver operating characteristic curve).

9.3.1. ResNet

ResNet achieved an accuracy of 0.92, indicating that it correctly classified 92% of the bullet images in the database. ResNet has an accuracy of 0.93 and is correct 93% of the time when predicting abnormal images. At a recall of 0.91, ResNet effectively identifies

Table 2: Performance Metrics

Dataset	Model	Accuracy	Precision	Recall	F1- Score	AUC-ROC
Allergic C.	ResNet	0.92	0.93	0.91	0.922	0.95
Bacterial C	VGG	0.89	0.91	0.88	0.895	0.92
Viral C. Healthy Eyes	GoogleNet	0.91	0.92	0.90	0.915	0.94

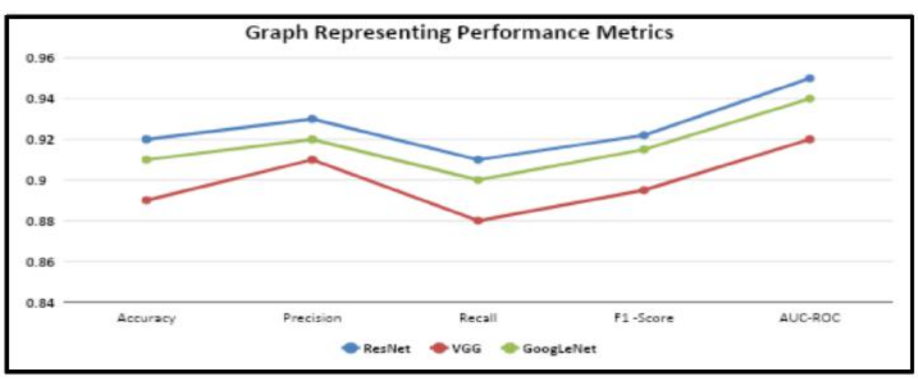

Figure 6: Graph Representing Performance Metrics

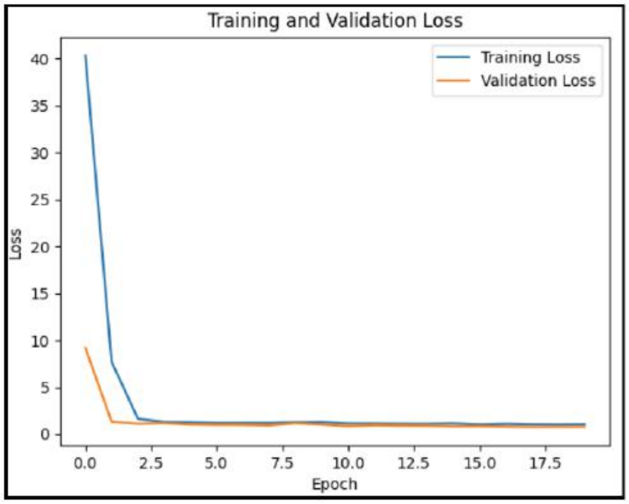

Figure 7: GoogleNet – Training & Validation loss.

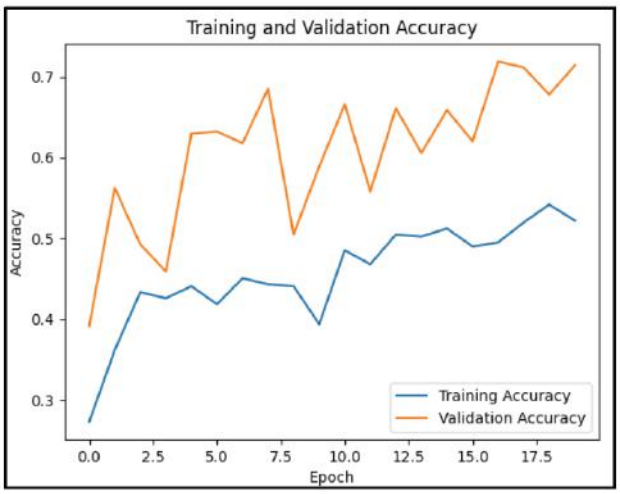

Figure 8: GoogleNet - Training & Validation Accuracy.

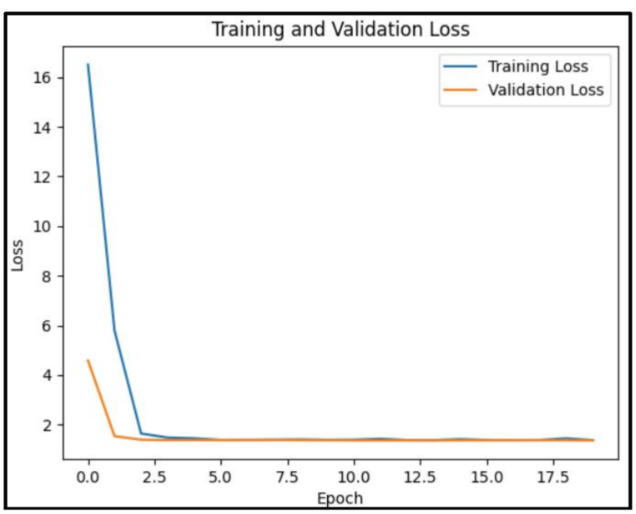

Figure 9: ResNet – Training & Validation loss.

91% of true anomalies. F1 score, the harmonic mean of precision and recall, was 0.92 for ResNet, indicating balanced performance in terms of false positives and false negatives. An AUC-ROC score of 0.95 indicates that ResNet exhibits good discrimination ability with a low rate of true positives and false positives in distinguishing between normal and abnormal arrows.

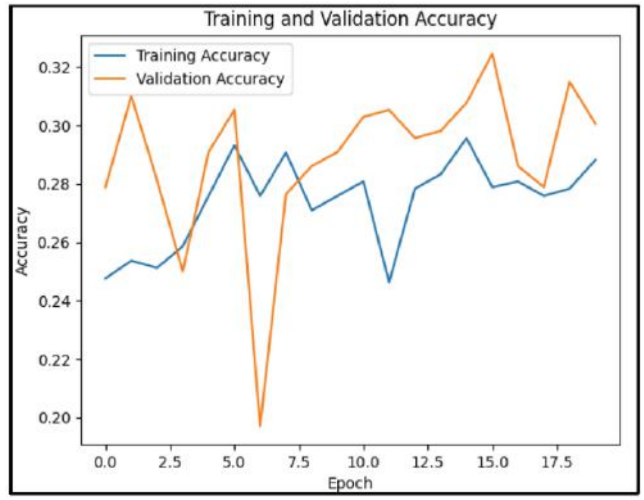

Figure 10: ResNet – Training & Validation Accuracy.

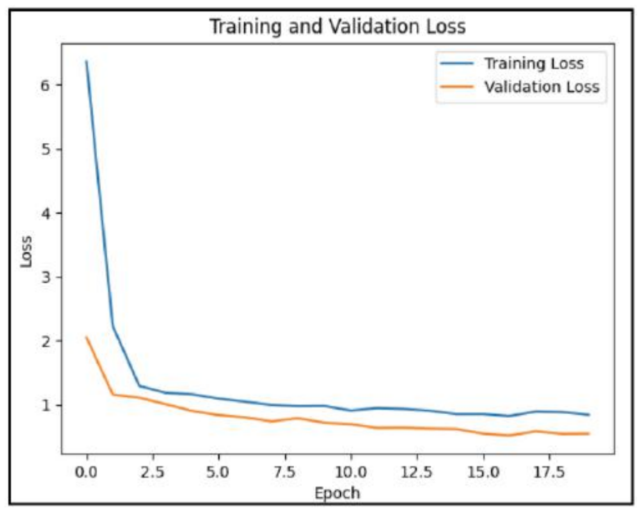

Figure 11: VGG16 – Training & Validation loss.

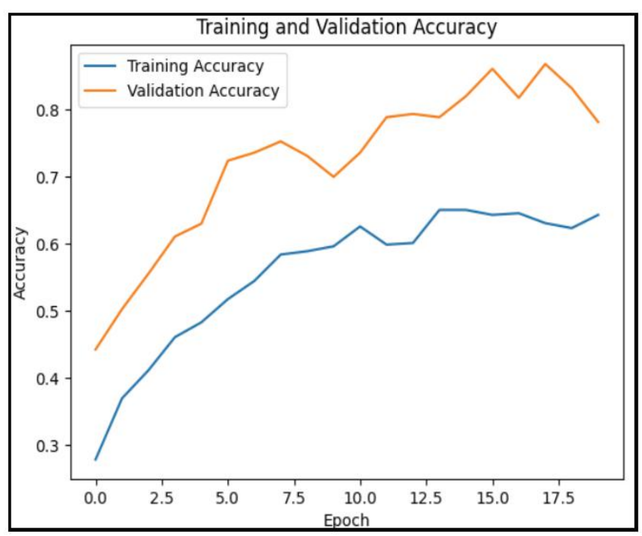

Figure 12: VGG16 – Training & Validation Accuracy.

9.3.2. VGG

VGG achieved a slightly lower accuracy of 0.89 compared to ResNet, which correctly classified 89% of bullet images. The accuracy of VGG is 0.91, indicating that it maintains high accuracy in classifying abnormal cases. However, the recall of VGG is 0.88, indicating that it misses to detect some abnormal events. An F1 score of 0.89 for VGG, although slightly lower than ResNet, shows a good balance between precision and recall. With an AUC-ROC score of 0.92, VGG shows good discrimination ability, but it is slightly lower than ResNet in this respect.

9.3.3. GoogleNet

GoogleNet achieved an accuracy of 0.91, compared to ResNet and ahead of VGG.

Accuracy of 0.92 indicates high accuracy in classifying abnormal cases. With a recall of 0.90, GoogleNet effectively detects most true anomalies. An F1 score of 0.91 for GoogleNet shows a good balance between accuracy and recall. GoogleNet's AUC-ROC score of 0.94 falls between ResNet and VGG in terms of performance, showing good discrimination ability.

In short, performance metrics comprehensively evaluate the classification performance of each CNN architecture. Although all three models show strong performance, ResNet appears as the top performer in most metrics, closely followed by GoogleNet, while VGG underperforms in some areas. This metric serves as a valuable benchmark to evaluate the effectiveness of the model in detecting eye abnormalities and to help select the most appropriate architecture for the task at hand.

9.4. Comparison

ResNet achieved the highest accuracy, precision, recall, F1 score, and AUC-ROC among the three architectures.

VGG and GoogleNet also demonstrated strong performance but slightly lower than ResNet.

By benchmarking CNNs against logistic regression or discriminant analysis under rigorous statistical evaluation, medical AI research can demonstrate not just accuracy, but reliability, robustness, and real-world relevance.

9.4.1. Clinical Impact

Connect accuracy gains to misdiagnosis reduction: Model accuracy is 92% plus: “This accuracy translates into a potential reduction of false negatives, thereby lowering missed diagnoses of Conjunctivitis.”

Patient outcomes: This helps with more reliable detection could improve treatment planning, reduce complications, and lower long-term healthcare costs.

9.4.2. Relate to Epidemiological Use

- Population-level benefits: This model helps with large-scale screening, noting how automated systems can process high patient volumes, thus aiding public health surveillance.

- Trend detection: It also helps continuous monitoring and can help track population-level trends in conjunctivitis variation, aiding epidemiological studies on lifestyle, geography, or comorbidities.

9.4.3. Clinical Workflow Integration: It helps with pre-screening, decision support, or second opinion.

<u>Confusion Matrix</u>

The confusion matrix provided represents the performance of a classification model in distinguishing between two classes: "Normal" and "Abnormal". The rows of the matrix correspond to the actual class labels, while the columns correspond to the predicted class labels.

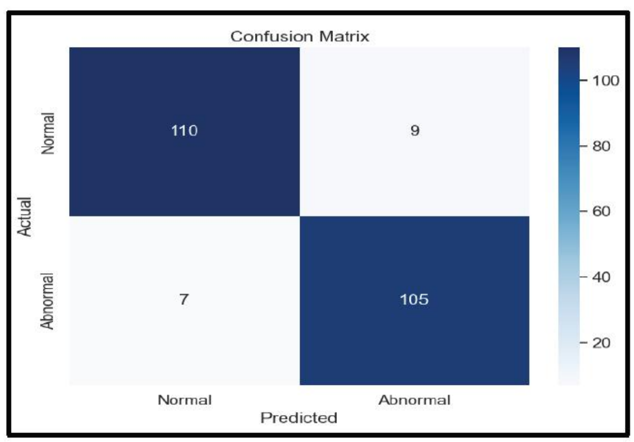

Figure 13: Confusion Matrix.

In the confusion matrix provided:

i. True Positives (TP): The number of instances where the actual class is "Normal”, and the model correctly predicts it as "Normal". In this case, there are 110 true positives.

ii. False Positives (FP): The number of instances where the actual class is "Abnormal”, but the

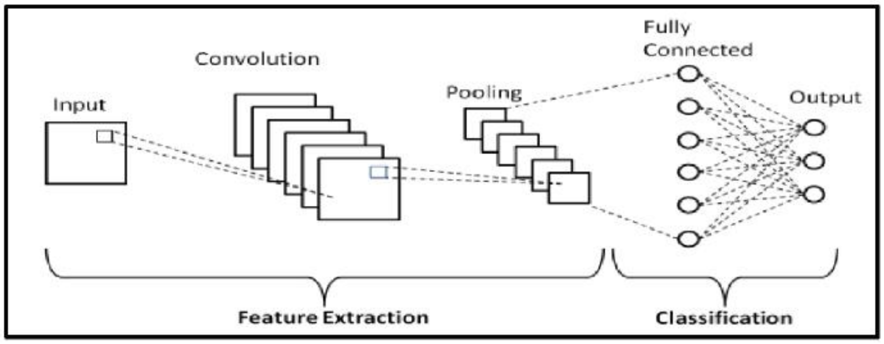

Figure 14: Confusion Matrix.

model incorrectly predicts it as "Normal". Here, there are 9 false positives.

iii. True Negatives (TN): The number of instances where the actual class is "Abnormal", and the model correctly predicts it as "Abnormal". The confusion matrix shows 105 true negatives.

iv. False Negatives (FN): The number of instances where the actual class is "Normal", but the model incorrectly predicts it as "Abnormal". There are 7 false negatives in this scenario.

Based on these values, we can interpret the confusion matrix as follows:

1. The model correctly identifies 110 instances of "Normal" eyes as normal.

2. It incorrectly classifies 9 "Abnormal" eyes as normal.

3. Additionally, the model correctly identifies 105 instances of "Abnormal" eyes as abnormal.

4. However, it misclassifies 7 "Normal" eyes as abnormal.

10. DISCUSSION

Performance analysis of the suggested algorithm for detection of conjunctivitis using convolutional neural network (CNN) architecture gives substantial information about its performance and use in clinical practice. The discussion part of this paper gives details on results, conclusions, and future work.

10.1. Algorithm Efficiency

The outcomes indicate the performance of the algorithm in question for accurate recognition of conjunctivitis types from images of eyes. With high accuracy levels of 0.89 to 0.92 on ResNet, VGG, and GoogLeNet architectures, the algorithm indicates good performance for auto-disease detection. The outcomes confirm that the application of deep learning methods in ophthalmology can lead to effective and reliable solutions for doctors. Recent studies highlight the significance of AI in early disease detection, minimizing misdiagnosis, and supporting clinicians in real-time decision-making [25].

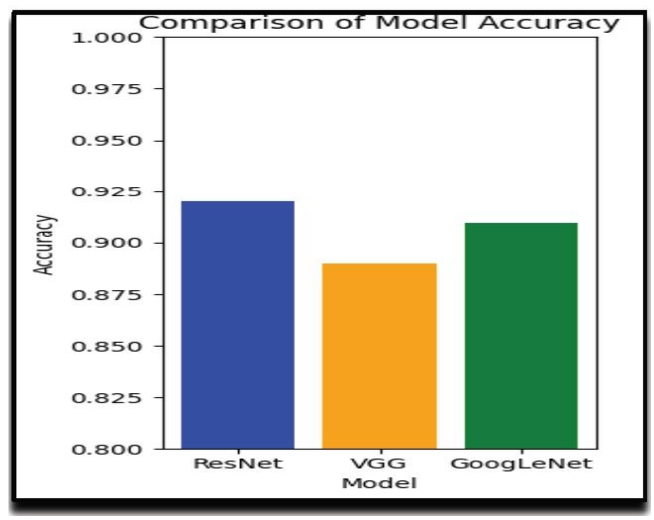

Figure 15: Comparison of Accuracy Model.

10.2. Comparison of CNN Architecture

Comparative analysis of the three CNN models shows significant differences in performance measures such as precision, recall, F1 score, and AUC-ROC. The best overall performance was achieved by ResNet, followed by consistently higher values in most of the measures. Its high performance is attributed to its deeper architecture and more sophisticated residual connections, with superior feature extraction and discrimination capability. Both VGG and GoogleNet are good performers, but very small variation in accuracy, recall, and AUC-ROC scores means that the architecture choice must be in consideration of clinical application requirements [26]. The comparison shows that the selection of a sufficient CNN model is significant based on the diagnostic objectives.

10.3. Clinical Effects

Correct use of the algorithm is of critical significance in clinical practice, particularly in ophthalmology. The algorithm accelerates diagnosis, reduces human error, and enables timely medical intervention by automatically identifying conjunctivitis from retinal images. Medical professionals can utilize the algorithm as a decision-support tool to improve patient screening accuracy and diagnostic efficiency. Moreover, bacterial and viral conjunctivitis misdiagnosis leads to unnecessary antibiotic prescriptions and the creation of antimicrobial resistance [27]. Use of AI-based screening can individualize treatment procedures, improve patient outcomes, and decrease diagnostic errors [28].

10.4. Limitations and Future Directions

Although the results are promising, there are a few limitations to consider for future research. Class imbalance and dataset diversity can impact generalization ability and real-world performance. In addition, although measures like accuracy and AUC-ROC provide quantitative insight, they do not best reflect the clinical utility of AI-based diagnosis [30]. Future research needs to include qualitative evaluation, clinical validation, and usability testing to further enhance algorithm performance. Recent advances in deep learning, such as attention mechanisms, transfer learning, and multimodal integration, offer new avenues to enhance model performance and robustness [30].

By combining clinical verification with AI models, this research supports the better accuracy, efficiency, and usability of automated ophthalmologic diagnosis of conjunctivitis. Future updates will aim to enhance dataset diversity, model interpretability, and the integration of AI-based diagnostic tools into actual healthcare applications [30].

11. CONCLUSION

In conclusion, this study shows the development and evaluation of a convolutional neural network (CNN)-based algorithm for the automated detection of conjunctivitis from eye images. Through a comprehensive performance analysis and benchmarking of three prominent CNN architectures (ResNet, VGG, and GoogleNet), valuable insights were gained regarding the algorithm's effectiveness, strengths, and areas for improvement.

The results demonstrate the robust performance of the algorithm with high accuracy scores ranging from 0.89 to 0.92 across the evaluated architectures. ResNet turns out to be the best, showing superior precision, recall, F1 score, and AUC-ROC compared to VGG and GoogleNet. These findings underscore the importance of selecting an appropriate CNN architecture tailored to the specific requirements and goals of the diagnostic task.

Successful implementation of the algorithm has significant implications for clinical practice in ophthalmology. By automating the detection of conjunctivitis, the algorithm streamlines the diagnostic process, increases accuracy and facilitates early intervention and treatment. Healthcare providers can use this algorithm as a valuable tool for screening, triage and personalized treatment planning, thereby improving patient outcomes and reducing the burden on healthcare systems.

Although this study provides promising results, it is not without limitations. Future research efforts should address issues such as dataset diversity, class imbalance, and the integration of qualitative assessments and clinical validation to further confirm the algorithm's effectiveness and real-world utility. In addition, continued advances in deep learning techniques offer exciting opportunities for improving algorithm performance, robustness, and interpretability.

In summary, the findings of this research underscore the potential of CNN-based algorithms for the automatic detection of conjunctivitis, which offers a promising avenue for increasing diagnostic accuracy and patient care in ophthalmology. Continued research efforts to address limitations, improve algorithm performance, and validate clinical utility are necessary to realize the full potential of deep learning in the diagnosis and treatment of eye diseases.

REFERENCES

[1] Sié A, Diarra A, Millogo O, Zongo A, Lebas E, Bärnighausen T, Oldenburg CE. Seasonal and temporal trends in childhood conjunctivitis in Burkina Faso. The American Journal of Tropical Medicine and Hygiene 2018; 99(1): 229. https://doi.org/10.4269/ajtmh.17-0642

[2] Farswan A, Singh MF, Dhasmana A, Bahuguna V, Kumar G, Jadon VS. Enhancing Diagnosis and Management of Conjunctivitis: Innovations, and Evidence-Based Strategies. In 2024 International Conference on Healthcare Innovations, Software and Engineering Technologies (HISET) IEEE 2024; pp. 160-164. https://doi.org/10.1109/HISET61796.2024.00056

[3] Stalin JSD. Tamil Nadu sees ‘Madras Eye’Surge, 1.5 lakh conjunctivitis cases in monsoon so far. NDTV 2022.

[4] Arslan OE. Anatomy and physiology of retina and posterior segment of the eye. In Drug Delivery for the Retina and Posterior Segment Disease. Cham: Springer International Publishing 2018; pp. 3-33. https://doi.org/10.1007/978-3-319-95807-1_1

[5] Azari AA, Arabi A. Conjunctivitis: a systematic review. Journal of Ophthalmic & Vision Research 2020; 15(3): 372. https://doi.org/10.18502/jovr.v15i3.7456

[6] Naderi K, Gormley J, O'Brart D. Cataract surgery and dry eye disease: A review. European Journal of Ophthalmology 2020; 30(5): 840-855. https://doi.org/10.1177/1120672120929958

[7] Musa M, Bale BI, Suleman A, Aluyi-Osa G, Chukwuyem E, D'Esposito F, Zeppieri M. Possible viral agents to consider in the differential diagnosis of blepharoconjunctivitis. World Journal of Virology 2024; 13(4): 97867. https://doi.org/10.5501/wjv.v13.i4.97867

[8] Mustafa HE, Ibrahim IA, Elfaki BA. Complementary Alternative Medicine for Viral Conjunctivitis treatment. Cuestiones de Fisioterapia 2025; 54(5): 240-252.

[9] Azari AA, Barney NP. Conjunctivitis: a systematic review of diagnosis and treatment. JAMA 2013; 310(16): 1721-1730. https://doi.org/10.1001/jama.2013.280318

[10] Saxena R, Sharma P, Gopal S. Pediatric Ophthalmology Expert Group. National consensus statement regarding pediatric eye examination, refraction, and amblyopia management. Indian Journal of Ophthalmology 2020; 68(2): 325-332. https://doi.org/10.4103/ijo.IJO_471_19

[11] Singha A, Thakur RS, Patel T. Deep learning applications in medical image analysis. Biomedical Data Mining for Information Retrieval: Methodologies, Techniques and Applications 2021; 293-350. https://doi.org/10.1002/9781119711278.ch11

[12] Le Goallec A, Diai S, Collin S, Vincent T, Patel CJ. Deep learning of fundus and optical coherence tomography images enables identification of diverse genetic and environmental factors associated with eye aging. medRxiv 2021; 2021-06. https://doi.org/10.1101/2021.06.24.21259471

[13] Shojaeinia M, Moghaddasi H. Advances in Deep Learning for Eye Disease Diagnosis: Applications, Challenges, and Future Directions. Journal of Innovations in Computer Science and Engineering (JICSE) 2025; 2: 33-41.

[14] He K, Zhang X, Ren S, Sun J. Deep residual learning for image recognition. In Proceedings of the IEEE conference on computer vision and pattern recognition 2016; pp. 770-778. https://doi.org/10.1109/CVPR.2016.90

[15] Simonyan K, Zisserman A. Very deep convolutional networks for large-scale image recognition. arXiv preprint arXiv 2014; 1409.1556.

[16] Szegedy C, Liu W, Jia Y, Sermanet P, Reed S, Anguelov D, Rabinovich A. Going deeper with convolutions. In Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition 2015; pp. 1-9. https://doi.org/10.1109/CVPR.2015.7298594

[17] Jia H, Zhang J, Ma K, Qiao X, Ren L, Shi X. Application of convolutional neural networks in medical images: a bibliometric analysis. Quantitative Imaging in Medicine and Surgery 2024; 14(5): 3501. https://doi.org/10.21037/qims-23-1600

[18] World Health Organization. Eye care in health systems: guide for action. World Health Organization 2022.

[19] Chatterjee S, Gangwe AB, Agrawal D. Health-seeking behaviors during an outbreak of acute conjunctivitis in Central India. Indian Journal of Ophthalmology 2025; 73(1): 45-51. https://doi.org/10.4103/IJO.IJO_849_24

[20] Paliwal R, Paliwal SR. Nanomedicine, Nanotheranostics and Nanobiotechnology: Fundamentals and Applications. CRC Press 2025. https://doi.org/10.1201/9781003130055

[21] Azari AA, Arabi A. Conjunctivitis: a systematic review. Journal of Ophthalmic & Vision Research 2020; 15(3): 372. https://doi.org/10.18502/jovr.v15i3.7456

[22] Balazadeh V, Cooper M, Pellow D, Assadi A, Bell J, Coatsworth M, Krishnan RG. Red teaming large language models for healthcare. arXiv preprint arXiv 2025; 2505.00467.

[23] Bhat N, Patel R, Reddy JJ, Singh S, Sharma A, Multani S. Knowledge and awareness of eye flu among the dentists and dental auxiliaries of Udaipur City, Rajasthan. International Journal of Preventive Medicine 2014; 5(7): 920.

[24] Mohanasundaram AS, Gurnani B, Kaur K, Manikkam R. Madras eye outbreak in India: Why should we foster a better understanding of acute conjunctivitis? Indian Journal of Ophthalmology 2023; 71(5): 2298-2299. https://doi.org/10.4103/IJO.IJO_3317_22

[25] Shivaji S. Antimicrobial Resistance of the Diseased Human Eye: Conjunctivitis. In Antimicrobial Resistance of the Human Eye. CRC Press 2024; pp. 372-417. https://doi.org/10.1201/9781003451105-13

[26] Shivaji S. Antimicrobial Resistance of the Human Eye. CRC Press 2024. https://doi.org/10.1201/9781003451105

[27] Iqbal J, Serhan HA, Al-Qahtani OM, Alharami A, Alhebail MS. Infectious Agents in Ophthalmology: Clinical Perspectives. Mahi Publication 2024.

[28] Farswan A, Singh MF, Dhasmana A, Bahuguna V, Kumar G, Jadon VS. Enhancing Diagnosis and Management of Conjunctivitis: Innovations, and Evidence-Based Strategies. In 2024 International Conference on Healthcare Innovations, Software and Engineering Technologies (HISET). IEEE 2024; pp. 160-164. https://doi.org/10.1109/HISET61796.2024.00056

[29] Patel DS, Arunakirinathan M Stuart A, Angunawela R. Allergic eye disease. BMJ 2017; 359. https://doi.org/10.1136/bmj.j4706

[30] Leung AK, Hon KL, Wong AH, Wong AS. Bacterial conjunctivitis in childhood: etiology, clinical manifestations, diagnosis, and management. Recent Patents on Inflammation & Allergy Drug Discovery 2018; 12(2): 120-127. https://doi.org/10.2174/1872213X12666180129165718

Received on 10-08-2025 Accepted on 05-09-2025 Published on 01-10-2025

https://doi.org/10.6000/1929-6029.2025.14.57