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# AUTOMATED CONJUNCTIVITIS DETECTION USING XCEPTION MODEL WITH TRANSFER LEARNING

Machine Learning

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## ABSTRACT

Conjunctivitis, an inflammation of the conjunctiva, is a common eye condition often diagnosed through visual inspection, a method prone to subjectivity and inefficiency. This study explores the potential of deep learning, specifically the Xception convolutional neural network (CNN) architecture, for automated conjunctivitis detection. A dataset of eye images, compiled from a published research paper and supplemented with internet sources, was used to train and evaluate the model. The Xception model initialized with pre-trained ImageNet weights and fine-tuned for conjunctivitis classification. Data augmentation techniques were employed to enhance the model's robustness. Results demonstrated promising performance, with the model achieving a test accuracy of 95.16%, an AUC-ROC score of 0.9484, a precision of 0.9773, a recall of 0.9412, and an F1-score of 0.9143. While training and validation metrics suggested potential overfitting, the model's robust performance on the test set indicates the potential of deep learning for automated conjunctivitis detection, offering a promising avenue for more objective and efficient diagnosis.

## KEYWORDS

Xception model, deep learning, machine learning, transfer learning, eye, conjunctivitis.

## INTRODUCTION

Conjunctivitis, commonly known as pink eye [1], is an inflammation of the conjunctiva, the transparent membrane that lines the inner surface of the eyelids and covers the sclera (white part) of the eye [2]. This prevalent ocular condition can be caused by numerous factors, including bacterial, viral, and allergic reactions, leading to symptoms such as redness, itching, discharge, and discomfort [3][4]. Accurate and timely diagnosis is crucial for effective treatment and to prevent the potential spread of contagious forms of conjunctivitis. Traditional diagnostic methods often rely on visual inspection by healthcare professionals, which can be subjective, time-consuming, and may not always capture subtle indicators of the condition [5]. Furthermore, the availability of specialists and timely access to care can be limited, particularly in resource-constrained settings [6].

In recent years, deep learning has emerged as a powerful and promising tool for medical image analysis, demonstrating remarkable success in various applications, including disease detection and classification. Convolutional Neural Networks (CNNs), a class of deep learning algorithms, have proven particularly effective in extracting complex features from images and achieving high accuracy in image classification tasks [7]. Among the various CNN architectures, the Xception model, a variant of the Inception architecture, stands out due to its efficient use of depth wise separable convolutions, enabling it to learn intricate patterns from image data while maintaining computational efficiency [8].

This paper explores the potential of the Xception model for automated conjunctivitis detection from eye images. We propose a deep learning pipeline that leverages the Xception architecture, pre-trained on a large dataset (ImageNet), and fine-tuned on a curated dataset of eye images labeled as either healthy or conjunctivitis affected. By employing transfer learning and data augmentation techniques [9][10], we aim to develop a robust and accurate model capable of automatically classifying eye images, thereby assisting healthcare professionals in achieving more objective and efficient diagnoses. This automated approach has the potential to improve access to timely diagnosis, particularly in remote areas or where specialist expertise is limited and contributes to better patient outcomes. The subsequent sections of this paper detail the methodology employed, including data collection and preprocessing, model architecture and training, experimental results, and a comprehensive discussion of the findings, culminating in a conclusion and outlining potential future research directions.

## LITERATURE REVIEW

Mukherjee et al. [11] have developed a mobile healthcare application called iConDet to detect conjunctivitis, a common eye disease, using deep learning. The application uses a dedicated conjunctivitis dataset to train deep learning algorithms, achieving an accuracy of 84% in detecting the condition. However, the accuracy is not perfect, as 16% of users may receive false positive or false negative results. Users should be aware of this potential issue to ensure accurate diagnosis and treatment.

Akram & Debnath [12] presents an automated eye disease recognition system that uses digital image processing and machine learning to identify and classify features from captured facial images. The system, which uses Deep Convolutional Neural Network (DCNN) and Support Vector Machine (SVM), outperforms existing methods in accuracy and specificity, achieving an average accuracy of 98.79%, sensitivity of 97%, and specificity of 99%.

Mondal et al. [13] investigates the effectiveness of deep learning frameworks in classifying conjunctivitis, a common eye ailment, using a dataset of 210 images. Three frameworks, VGG19, ResNet50, and Inception V3, were used. The results showed promising results, with VGG19 achieving 87.3% accuracy, ResNet50 reaching 93.6%, and Inception V3 achieving 95.2% accuracy, indicating the potential of deep learning frameworks for accurate diagnosis of conjunctivitis.

Erdin & Patel [7] classifies human eyes into four categories: trachoma, conjunctivitis, cataract, and healthy eye. A CNN model was augmented with additional layers to learn complex patterns from eye image data. The model achieved 88.36% accuracy, with 89.25% precision, 88.75% recall, and 88.5% F1 score. The system's ability to differentiate between healthy and diseased eyes and specific classifications of trachoma, conjunctivitis, and cataracts allows for targeted interventions and treatment plans.

Bitto & Mahmud [14] use Convolutional Neural Networks (CNNs) to classify eye diseases. It evaluates their effectiveness in healthcare using a custom dataset of 2250 images, with 1689 for training and 561 for testing. The focus is on identifying normal eyes, conjunctivitis, and cataracts. The researchers used three CNN models: VGG16, ResNet-50, and Inception-v3, with images resized to 224x224 pixels. Data augmentation was also used to enhance the dataset. Inception-v3 had the best accuracy at 97. 08% but took the longest time, while ResNet-50 and VGG16 had lower accuracy and longer processing times.

Bobade et al. [15] suggests a deep learning model for detecting eye issues like cataracts, conjunctivitis, cross eyes, and bulging eyes. The aim is to improve public awareness and early detection of these conditions. The approach uses digital image processing techniques to extract features from images, which are analyzed using Convolutional Neural Networks (CNNs) to classify eye diseases. In this research two models were trained, one for single-eye images and one for images of both eyes. To avoid overfitting, they used data augmentation. The model achieved 96% accuracy for single-eye images and 92. 31% for dual-eye images.

D. S. Singh et al. [16] propose a new method using Convolutional Neural Networks (CNNs) to detect the eye flu virus from eye images.

Called EyeFluNet, this model uses deep learning with a multi-layered structure for feature extraction and classification, identifying patterns that indicate flu infection. Pooling layers reduce feature size while keeping crucial details, and non-linear activation functions help learn complex relationships. EyeFluNet has shown an 88% accuracy in distinguishing infected eyes from healthy ones, indicating its potential as a reliable tool for early flu identification. Further research needed for clinical application.

O. Singh et al. [17] aims to create a CNN model to identify and classify eye flu conditions from eye images. Using deep learning, the model learns to differentiate between healthy eyes and those with eye flu by analyzing complex patterns. The process involves using an ImageDataGenerator to prepare and augment the images, which helps improve the model's performance. The CNN model achieved 90% accuracy but does not indicate if validation was done on a separate dataset.

Li et al. [18] examined ways to improve classification performance by deepening neural networks through more layers and nodes. Many classifiers struggle with new datasets, limiting their effectiveness. The authors propose a new method using an Auto-Encoder (AE) model. An AE compresses data into a lower-dimensional format and reconstructs it. The compressed data helps traditional classifiers work better. Experiments on conjunctivitis and STL-10 datasets showed that the AE model improved accuracy and reduced the False Positive Rate.

Soysa & De Silva [19] introduces "Eye Plus," a mobile app for self-checking eye diseases like cataracts and conjunctivitis. It uses pre-trained models to analyze images and employs a G-filter for better image quality. While it has 83.3% accuracy, the study notes limitations regarding performance across different ethnicities and ages. Challenges in maintaining camera distance and image adjustments may affect results.

## METHODOLOGY

We detected conjunctivitis with the Xception convolutional neural network (CNN) architecture using a dataset of eye images, both affected and normal. The model trained in exactly two phases to get the single best performance. In the first phase, we decisively leveraged transfer learning [20] by initializing the Xception model with ImageNet pre-trained weights. We then carefully froze all base layers and added custom top layers [21]. In the second phase, we unfroze all layers and used a lower learning rate, allowing the pre-trained weights to adjust to our specific dataset, to fine-tune the entire network. This methodology employed transfer learning along with data augmentation to find conjunctivitis in eye pictures reliably and accurately.

### Data Collection

The dataset for this study contains a lot of images from some main sources. A meaningful portion of the data originated from the research paper [11]. That data comprised a large amount. This was the only primary source. Furthermore, images from many online locations were gathered to make our dataset quite diverse and strong. These images were carefully selected and annotated to guarantee they matched the current dataset.

The total number of images is 582. The complete augmented dataset was then separated into three special subsets: training, testing and validation. The images were resized to a consistent 299x299 pixels to meet the Xception model's input needs. We combined data from both sources to improve the model's accuracy and its ability to work in different real-world situations when looking for conjunctivitis.

### Pre-processing image

The model gained better generalization capabilities and adapted to real-world conditions by data augmentation methods. Training dataset diversity grows because these techniques are used. Data augmentation used various methods such as pixel value rescaling to [0, 1] and randomly rotating along with width and height changes, shearing, and zooming along with horizontal image flipping and brightness adjustment [22]. By applying augmentation techniques to the dataset, it became more diversified thus creating a stronger training dataset that reduces model overfitting risks while boosting performance on new data inputs. The adopted image processing used standard RGB (Red, Green, Blue) color representation due to its widespread use in digital imaging. The digital picture contains three values per pixel which show the amount of red and blue along with green intensities. Each pixel intensity varies from zero to two hundred fifty-five scales where zero means no intensity and two hundred fifty-five signifies complete intensity. Human vision patterns match the RGB format which has become the most common digital imaging standard.

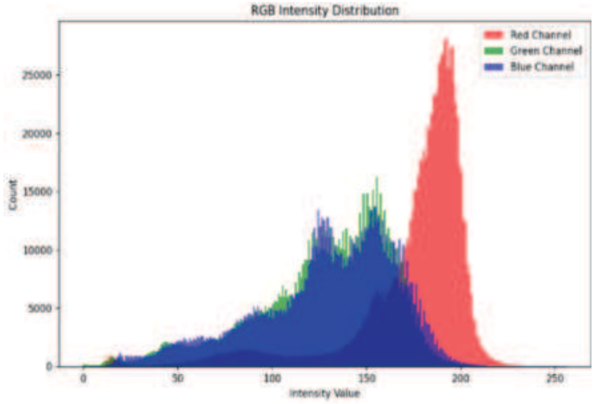


**Figure 1:** RGB Color Intensity Data Samples

## MODEL ARCHITECTURE

The proposed model architecture for conjunctivitis detection begins with an input layer designed to accept images of size 299 x 299 x 3, corresponding to the height, width, and color channels of the input images. These images have been pre-processed and augmented to enhance the model's ability to generalize new, unseen data.

To adapt the base model for the specific task of conjunctivitis detection, several custom top layers are added. The first is a Global Average Pooling layer (GlobalAveragePooling2D), which reduces each feature map from the base model's output to a single number by taking the average, resulting in an output shape of (2048,). This approach helps prevent overfitting and reduces the total number of parameters by eliminating the spatial dimensions of the feature maps. Following this, a Batch Normalization layer (BatchNormalization) is applied, which normalizes the outputs from the previous layer. This normalization accelerates training and improves performance by ensuring that the inputs to each layer have a consistent distribution.

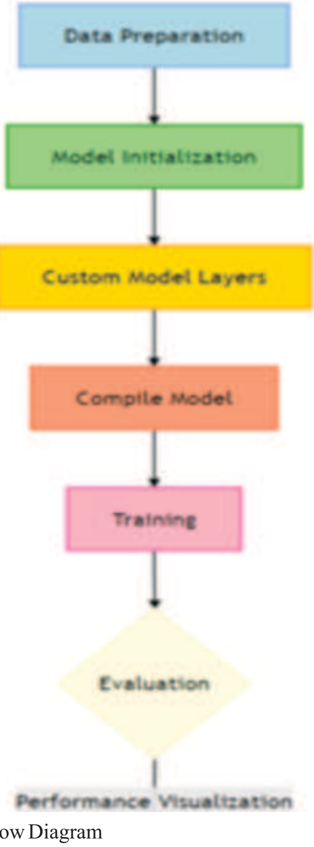


**Figure 2:** Workflow Diagram

The model benefits from an additional Dropout layer which uses a 50% rate (Dropout (0.5)) to improve generalization. The random zero-setting feature of this layer enhances model robustness because it reduces neural network dependence on any single input unit. After dropout the model includes another dense layer with 1,024 ReLU neurons so it can identify elaborate patterns enabled by the base model features (Dense (1024, activation='relu')). An additional application of Dropout (0.5) occurs on the dense layer output to sustain overfitting reduction. The last layer of the model consists of an Output layer that has one neuron with sigmoid activation function (Dense (1, activation='sigmoid')). The final output from the layer provides a value between zero and one to determine if the input belongs to the conjunctivitis-positive category or conjunctivitis-negative category.

A two-step process implements the training strategy. During phase one the model trains the custom top layers alongside freezing the base model to take advantage of its acquired feature representations. The model optimization runs with the Adam optimizer and 0.001 learning rate along with the binary cross-entropy loss function suited for binary classification. The main factor used to evaluate performance is accuracy. Ten epochs of the training process include performance-enhancing callbacks as part of the protocol. Early Stopping enables the system to spot no improvement in validation loss over 10 epochs resulting in early training termination thus avoiding overfitting. By applying the ReduceLROnPlateau callback the learning rate receives a 0.5 reduction when the validation loss remains stagnant for 7 epochs which enables the model to refine its adjustments. The best model according to validation accuracy is saved through a Model Checkpoint operation.

During phase two the model unfreezes both the base model together with all its layers so that the whole network receives fine-tuning under a learning rate of 0.0001. Model adjustments on pre-trained weights within the base model become possible during this step to better perform conjunctivitis detection. The training parameters stay the same in the second phase, but it takes another 10 epochs to execute.

**Table-1 Hyperparameters For Model Training**

| Component | Hyperparameter | Value(s) |
|---|---|---|
| Base Model (Xception) | Weights | "imagenet" |
| | Trainable Layers (Initial) | False (all layers initially frozen) |
| | Trainable Layers (Fine-tuning) | True (all layers unfrozen) |
| Custom Layers | Dropout Rate | 0.5 |
| | Dense Layer 1 Units | 1024 |
| | Dense Layer 1 Activation | ReLU |
| | Dropout Rate | 0.5 |
| | Output Layer Units | 1 |
| | Output Layer Activation | Sigmoid |
| Optimizer | Algorithm | Adam |
| | Learning Rate (Initial) | 0.001 |
| | Learning Rate (Fine-tuning) | 0.0001 |
| Metrics | | Accuracy |
| Training | Batch Size | 8 |
| | Epochs (Initial) | 15 |
| | Epochs (Fine-tuning) | 10 |

**Performance Matrix**

For evaluation, several metrics are employed to assess model performance comprehensively [23][24].

$$\begin{aligned} precision &= \frac{TP}{TP+FP} \\ recall &= \frac{TP}{TP+FN} \\ F1 &= \frac{2 \times precision \times recall}{precision + recall} \\ accuracy &= \frac{TP+TN}{TP+FN+TN+FP} \end{aligned}$$

**EXPERIMENT AND RESULT**

The model trained for 20 epochs achieved a peak training accuracy of 0.9714 and achieved a minimum training loss of 0.0746 at the expense of fluctuating validation metrics that reached 0.3731 and 0.9088. The test results produced accuracy at 0.9516 along with a loss rate of 0.1841. AUC-ROC was 0.9484, precision 0.8889, recall 0.9412, and F1-score 0.9143. The model achieved 0.91 and 0.97 Class 1 and 0 F1-Scores within the training results. The model demonstrated robust performance with training data, yet the validation metrics showed indications of overfitting.

**Table-2 Classification Report**

| | Precision | Recall | F1-Score | Support |
|---|---|---|---|---|
| 0 | 0.98 | 0.96 | 0.97 | 45 |
| 1 | 0.89 | 0.94 | 0.91 | 17 |
| Accuracy | | | 0.95 | 62 |
| Macro Avg | 0.93 | 0.95 | 0.94 | 62 |
| Weighted Avg | 0.95 | 0.95 | 0.95 | 62 |

During 38 epochs of analysis the training accuracy reached 1.0 yet the validation accuracy stabilized around 0.9 with occasional variations. After overfitting occurs the model demonstrates adequate generalization capabilities. Regularization is recommended.


**Figure 3:** Training and Validation Accuracy

Training and validation loss across 38 epochs show training loss decreasing to under 0.2 (with a spike at epoch 20) and validation loss decreasing to 0.4 with fluctuations. The difference between the curves again points to overfitting. The epoch twenty spike warrants investigation. Regularization is recommended.


**Figure 4:** Training and Validation Loss

The AUC value of 0.95 in the ROC curve supports excellent binary classification because it indicates a balanced performance between true and false positive rates.

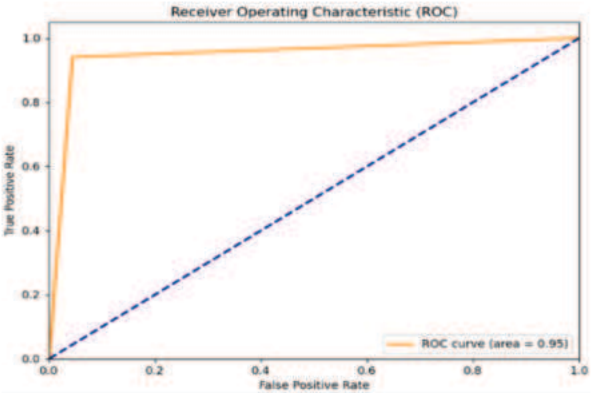


**Figure 5:** ROC Curve

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The confusion matrix demonstrates high accuracy rates because it corrects forty-three out of forty-five class 0 instances and all 16 out of 17 class 1 instances. The model displays an accuracy level of 95.16% while achieving excellent precision alongside recall for each classification category.

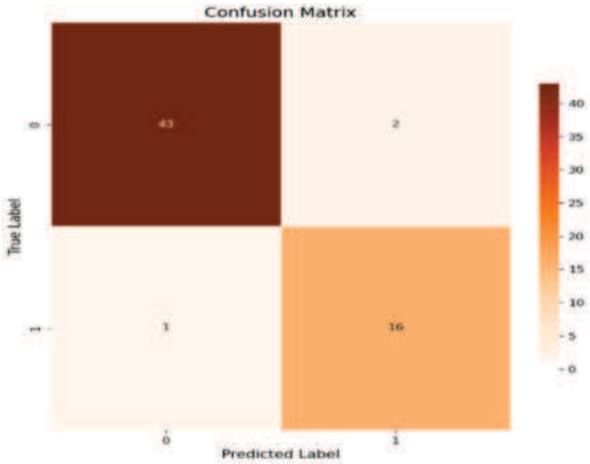


**Figure 6:** Confusion Matrix

**Table-4 Comparison Of Different Methods**

| Reference | Evaluation Metrics | Method Used | Best Results |
|---|---|---|---|
| [11] | Cohen's Kappa | EfficientNet | 84% |
| [16] | Precision, Recall and F1-Score | CNN | 88.60% |
| Proposed model | Accuracy, Precision, Recall and F1-Score | Xception model | 97.73% |

## DISCUSSION

Multiple vital metrics and visualizations form the basis of a complete binary classification model performance evaluation. The learning process becomes clear from observing the training and validation loss curves because they demonstrate decreasing loss values during epochs. The model needs stable resolution of this sudden increase to achieve stability. The accuracy patterns duplicate the loss trends because training accuracy reaches 1.0 while validation accuracy maintains at 0.9. A gap exists between these results that shows problems related to overfitting. The model operates at high validation accuracy although this number falls behind training accuracy which shows the model lacks widespread adaptability. The inconsistent pattern of validation accuracy indicates both data noise factors and localization problems that might prevent the model from processing new data effectively. The ROC curve establishes a better understanding of how the model functions. The model demonstrates exceptional discrimination capabilities because its AUC score measures 0.95. As the curve moves into the top-left area it shows how favorably both the true positive rate, and the false positive rate relate to each other. The model demonstrates aptness for accurate prediction despite its known overfitting problems.

A confusion matrix presents precise information regarding how the model classifies data. A total of 43 correct assignments were made for class 0 while 16 correct assignments were made for class 1 which demonstrates the model's effective performance. The assessment shows that the model generates only a minimum number of errors across its classifications. This conclusion gets additional support from the precision and recall calculations as well as the accuracy values. The accuracy metrics have limited use because class imbalances can affect their validity. The class distribution remains unspecified in the provided data, but the similar instance counts for each class demonstrate this issue might not affect the model performance.

## CONCLUSION

Model performance evaluation found substantial metrics throughout all categories during analysis. According to model calculations the accuracy reaches 95.16% which demonstrates the model performs well in making accurate classifications. Precision measures 97.73% while recall reaches 95.56% for identifying class 0 members which indicates the model's success at accurately recognizing class 0 elements and retrieving most actual class 0 samples. The accuracy obtained from class 1 reached 88.89% precision and 94.12% recall. Based on the provided precision and recall values it is possible to deduce that the F1-score exhibits prominent levels. The ROC curve analysis revealed a discriminating power of 0.95 thus proving that the model effectively detects differences between classes across multiple threshold points. Among all metrics evaluated the best result was a precision value of 97.73% for class 0 which shows how effectively the model protects against false positive identifications within this class. The model demonstrates excellent effectiveness as a solution for its targeted classification task.

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