Conjunctivitis Detection: A Comprehensive Review of Deep Learning Approaches

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ABSTRACT

Background: Conjunctivitis, often referred to as "pink eye" is a highly prevalent inflammation of the conjunctiva, a thin, transparent membrane lining the white part of your eye and the inner surface of your eyelids. This inflammation triggers a cascade of symptoms that can range from mild annoyance to significant discomfort, affecting people of all ages worldwide. The three main types of conjunctivitis are viral, bacterial, and allergy. Some common symptoms include redness of the white part of the eye, ranging from watery to thick and pus-like, discharge from the eye, itching or burning sensation, and a Gritty feeling in the eye.

Methods: Several deep-learning techniques for conjunctivitis detection have been developed due to their simplicity of use and their affordability. This systematic review delves into the burgeoning field of machine learning within healthcare, specifically seeking viable approaches for detecting conjunctivitis. We embark on a comparative analysis of the most successful ML algorithms currently in use regarding machine learning, including evaluation metrics, image augmentation, and the origin and size of the dataset used. Results: The results of this study provide compelling evidence for the feasibility and potential benefits of using DL algorithms for conjunctivitis detection. Conclusion: This review sheds light on the potential of machine learning in detecting Conjunctivitis, providing scientific evidence for its feasibility. By analyzing images, diagnoses, and clinical data within the medical field, the review explores how machine and deep learning algorithms can offer a wide-ranging approach to conjunctivitis detection.

Key Words: Conjunctivitis, eye flu, machine learning, deep learning, pink eye, CNN.

1. INTRODUCTION

Conjunctivitis, a frequent visitor in ophthalmology clinics, shouldn't be solely treated based on its typical symptoms. While redness, irritation, and discharge are common culprits, be wary of the masqueraders! Severe pain, blurred vision, and a pupil sensitive to light shouldn't be ignored [1]. Viral conjunctivitis highlights the dominance of viruses, particularly adenovirus, enterovirus, and herpes virus, as the primary causative agents, collectively contributing to 80% of all cases of acute conjunctivitis [2]. Allergic conjunctivitis is a prevalent immunological hypersensitivity disorder affecting up to 40% of the population. Despite its prevalence, it is often underdiagnosed and undertreated, with only 10% of patients seeking medical attention while others resort to over-the-counter medications and non-pharmacological remedies [3]. Bacterial conjunctivitis, predominant in children, manifests with purulent discharge and eyelid mattering, often warranting individualized antibiotic treatment for uncomplicated cases [4].

Additionally, there is a risk of transmission from an infected individual to others, highlighting the importance of preventive measures and prompt medical intervention to mitigate the spread of eye infections [5]. Limited access to specialist doctors in remote areas poses challenges for residents seeking diagnosis and treatment for eye-related issues [6]. Allergic conjunctivitis necessitates the removal of irritants, cool compresses, and the use of artificial tears.

Bacterial conjunctivitis is effectively treated with antibiotic eye drops, while viral conjunctivitis may require the use of steroids [7]. Given the high contagion of Adenoviral Conjunctivitis, it is imperative to enforce quarantine measures in ophthalmology clinics and doctor's offices, necessitating an automated and non-invasive approach [8].

Distinguishing conjunctivitis from other conditions causing a "red eye" is crucial due to the potential for severe consequences affecting vision or even posing life-threatening risks. Conditions such as acute angle-closure glaucoma, uveitis, endophthalmitis, carotid-cavernous fistula, cellulitis, and anterior segment tumors can manifest with similar symptoms. Recognizing these distinctions is essential for prompt and appropriate medical intervention to prevent adverse outcomes [9]. The increasing incidence of eye flu, or conjunctivitis, in India during the rainy season has become a significant public health concern. Reports indicate a surge in cases, with Delhi-NCR, Agra, Maharashtra, Kerala, Haryana, and Bihar experiencing substantial outbreaks [10].

Delhi faced an unprecedented flood on July 27th, 2023, marking the most severe recorded incident in the last four decades. The Yamuna River's water levels reached unprecedented heights, resulting in extensive waterlogging that significantly disrupted both communities and infrastructure throughout the city. In the aftermath of this calamity, there has been a notable 10-15% surge in conjunctivitis cases compared to previous years [11]. For individuals experiencing persistent symptoms and signs unresponsive to routine pharmacotherapy, allergen immunotherapy stands out as a crucial treatment alternative. The underlying principle involves desensitizing the body to specific allergens responsible for activating the immune system and inducing allergy symptoms [12].

The detection of conjunctivitis still poses a lot of challenges which implies that there is a continuous need for research as well as literature reviews to come up with new and efficient ways of identification. Initially, distinguishing between numerous species of conjunctivitis such as viral and bacterial could be a problem for physicians not using laboratory tests. This may result in inappropriate therapy method selection especially whereby there will be high utilization of unnecessary antibiotics, which in turn results in the development of antibiotic resistance. Rigorous evaluation of the most recent research conducted in eye disease diagnostics is essential for us to continue to enhance accuracy in detection, identify effective and convenient treatment avenues, and proactively protect the sight and wellbeing of people living with conjunctivitis.

Our research aims to analyze recent advancements and concepts in applying machine learning to healthcare. Specifically, we'll focus on identifying promising approaches for accurately detecting conjunctivitis through medical image analysis. Furthermore, we'll compare the performance of leading machine learning algorithms used in such studies. This comparison will encompass the machine learning techniques employed, evaluation metrics used, image augmentation methods applied (if any), dataset origin, size, and the study that achieved the highest accuracy.

Table 1: Questions addressed in our literature review

Addressed Questions
1. What was the total number of images included in the dataset for this study? 2. Among machine learning algorithms, which ones have proven to be the most effective in identifying conjunctivitis disease using images? 3. What is the level of precision achieved by machine learning algorithms in diagnosing conjunctivitis using image data?

2. LITERATURE REVIEW

Conjunctivitis, a common and contagious eye disease characterized by inflammation of the outer membrane of the human eye, can be effectively controlled and treated with medication depending on its specific type. Recognizing its potential link to other viral diseases, including COVID-19, researchers have emphasized the importance of timely detection in this study.

Table 2: Comparative analysis of Conjunctivitis

Reference of paper	Method	Evaluation Metrics	Image Augmentation used	Data Augmentation Methods	Source of Dataset	Volume of Dataset	Achieved accuracy	Conclusion
[13]	CNN architecture used: EfficientNet	Cohen's Kappa	Yes	Rotation and Flipping	Self-collected from internet	150	84%	Model detected conjunctivitis with accuracy of 84%

[14]	DCNN, SVM	Sensitivity, Specificity	No	N/A	ICEH, University of Rochester, UCSD School	249	98%	DCNN outperforms SVM models
[15]	VGG-19, ResNet-50, and Inception V3	Precision, F1 score, Accuracy	Yes	Flipping, Rotation, Cropping	Not indicated	25	97%	InceptionV3 had a higher accuracy of 97%
[16]	CNN	Accuracy, recall, precision, f1 score	Yes	Not mentioned	Multiple websites	653	88%	Fine Tuning is required to enhance CNN model accuracy
[17]	VGG-19, ResNet-50, and Inception V3	Accuracy, precision, f1 score, TPR, TNR, FPR, FNR	No	N/A	Shutter stock and the google website	2250	97.86%	Inception-v3 performs the highest accuracy with 97.86%
[18]	DCNN	Accuracy	Yes	Rotation and Flipping	Nearby optometrist	1200	92%	Model detected disease with 92% accuracy
[19]	CNN	Precision, recall and f1 score	Yes	Not mentioned	Not indicated	3000	88.60%	Accuracy of 88.60%
[20]	CNN	precision, recall, and F1- score, accuracy	No	N/A	Not indicated	Not mentione d	90%	The obtained accuracy is 90%
[21]	CNN	precision, recall, and F1- score, accuracy	No	N/A	Not indicated	Not mentione d	90%	The obtained accuracy is 90%

[22]	CNN	Accuracy	No	N/A	Not indicated	150	83.33%	The obtained accuracy is 83.33%

Mukherjee et al. [13] designed a mobile healthcare application named iConDet, enabling users to perform an initial level of conjunctivitis detection, a contagious eye disease. The development of iConDet leverages the power of deep learning, a subset of machine learning that utilizes artificial neural networks to learn from data. The researchers created a dedicated conjunctivitis dataset to train the deep learning algorithms within the application. By exposing the deep learning model to this extensive dataset, the researchers equipped it with the ability to recognize patterns and features associated with conjunctivitis in new, unseen images. The application utilizes deep learning techniques trained on a specially prepared conjunctivitis dataset, achieving an accuracy of 84% in detecting the condition. The accuracy is, while encouraging, but is not perfect, it is essential to acknowledge that the remaining 16% of users might receive either false positive (incorrectly diagnosed with conjunctivitis) or false negative (incorrectly diagnosed as healthy) results. and users should be aware of the possibility of receiving incorrect results.

Akram & Debnath [14] proposed a system for automated eye disease recognition that utilizes machine learning techniques for image analysis. First, facial features are detected using HOG feature selection and a linear SVM classifier to identify faces. Then, landmarks are used to locate and extract eye regions, which are pre-processed to a standard size. For disease classification, two approaches are explored: a Deep Convolutional Neural Network (DCNN) and a Support Vector Machine (SVM) with a Radial Basis Function (RBF) kernel. The DCNN architecture is inspired by successful CNN models for recognition tasks, featuring convolutional and pooling layers for feature extraction followed by fully connected layers for classification. The SVM offers an alternative classification method suitable for non-linear problems. To train and evaluate these models, a custom dataset of 1753 eye images from various sources is created, encompassing seven different eye diseases. The images are pre-processed for consistency and include examples of visual abnormalities like blurred lens, spots on the cornea, and redness.

Mondal et al. [15] investigates the effectiveness of state-of-the-art deep learning models (VGG-16, ResNet-50, InceptionV3) for conjunctivitis classification using a customized clustering approach and its potential as a diagnostic aid. The study leverages transfer learning to train the models and utilizing pre-trained weights from existing architectures. To address potential overfitting due to limited data, the authors employ data augmentation techniques like resizing, cropping, flipping, rotating, and resizing images. A novel approach involving DBSCAN clustering is proposed. The pre-processed data is divided into clusters based on feature similarity. Subsequently, each cluster is used to train the three deep learning models (VGG-16, ResNet-50, InceptionV3) with hyperparameter tuning via Keras Tuner. This ensures the selection of the best performing model for each cluster. The framework's performance is evaluated using metrics like Area Under the Curve (AUC) from Receiver Operating Characteristic (ROC) curves.

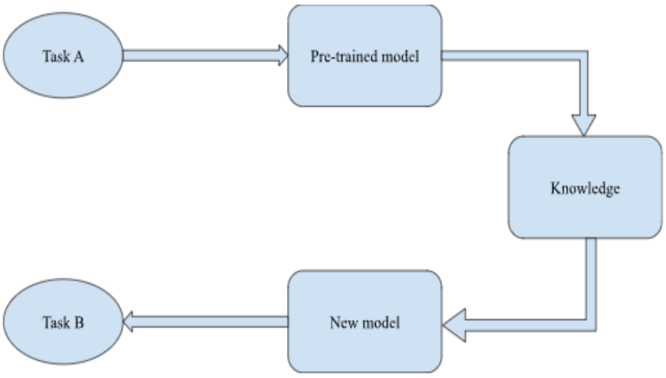

Figure 1: Transfer Learning approach

Erdin & Patel [16] examines a pre-trained CNN model to classify cataracts, conjunctivitis, trachoma, and healthy eyes. An open-source image dataset in split for training, validation, and testing. While using publicly available data is common, the authors consider the quality and labeling accuracy of these sources. The image pre-processing state utilized a standard train-validation-test split to prevent overfitting, but converting images to grayscale might discard useful color information. The CNN architecture employs convolutional and pooling layers for feature extraction and dimensionality reduction, along with ReLU activation, which are all standard components. However, the specific architecture details can significantly impact performance. Referencing successful CNN architectures and hyperparameter tuning could optimize these parameters. The model's performance is evaluated using a confusion matrix, a common practice that provides insights into various classification outcomes. From this matrix, metrics like accuracy and F1 score can be calculated.

Bitto & Mahmud [17] explores transfer learning with pre-trained models to identify eye diseases (cataracts, conjunctivitis, normal). They also utilized Transfer learning with pre-trained models. They acknowledge the importance of high-quality data and medical verification but gather data from websites like Shutterstock (potential weakness). They address this by having a medical professional confirm the data and split it for training and testing. Standard pre-processing techniques like resizing and flipping are applied to augment the data. The core of the model is Transfer learning, where pre-trained models VGG16, ResNet50, and InceptionV3 are used (fig. 3.4). The paper explains the rationale behind transfer learning and details the architecture of each pre-trained model. To evaluate the model's performance, the authors plan to use various metrics based on the confusion matrix, a standard practice in classification tasks.

Bobade et al. [18] combines image processing techniques with a custom CNN architecture for eye disease classification. Beyond standard image processing tasks like compression and enhancement, the authors perform data collection, resizing, normalization, and augmentation. Data is gathered from various sources including Kaggle and optometrists, covering five eye conditions (conjunctivitis, cataract, uveitis, bulging eyes, crossed eyes). To prevent overfitting due to limited data, they employ five data augmentation strategies (rotation, flipping). The collected images have various sizes, so they are pre-processed to a uniform dimension of 200x200 pixels. The core model is a CNN with nine layers. Three convolutional layers with increasing filter numbers (16, 32, 64) and a "linear" activation function are used for feature extraction. The Adam optimizer is chosen for training, and the data is split 80/20 for training and validation. Training utilizes 30 epochs and 50 batches. Overall, this approach combines data acquisition, pre-processing, augmentation, and a custom CNN architecture for eye disease classification.

D. S. Singh et al. [19] tackling normal eye vs. Red-eye classification using a deep learning approach. It emphasizes the importance of a high-resolution and diverse dataset encompassing various eye angles, lighting condition, age groups, and red-eye severities. To ensure model generalizability, data preprocessing involves image annotation, normalization (size, orientation, color), and potentially removing artifacts. The data is then split into training, validation, and testing sets, with a balanced representation of both normal and red eye in the training set. A Convolutional Neural Network (CNN) architecture is proposed for the model, utilizing convolutional and pooling layers for feature extraction and fully connected layers for classification. The model will be trained using the training data and fine-tuned using the validation set to prevent overfitting. Finally, the model's performance will be evaluated on a separate testing set using metrics like accuracy, precision, and recall. By analyzing misclassifications and areas for improvement, the authors aim to refine the model for better normal vs. red-eye classification.

O. Singh et al. [20] focuses on developing a CNN model specifically designed to identify and classify eye flu conditions from ocular images. By leveraging deep learning, the model can learn complex patterns within these images that differentiate between healthy eyes and those infected with eye flu. The methodology revolves around constructing a CNN architecture tailored to capture the intricate visual features associated with eye flu symptoms. However, the researcher might not specify the size and diversity of the image dataset used to train the CNN model. The model development process involves some key steps. First, an ImageDataGenerator is used to pre-process and augment the image data. This process helps prepare the images for the CNN model and potentially improve its generalizability by creating variations of existing images. Following pre-processing, the CNN architecture itself is designed. The researchers meticulously designed the architecture to effectively capture the subtle visual characteristics of eye flu. This focus on capturing relevant features is critical for achieving high accuracy in differentiating between healthy and diseased eyes. The model achieved an accuracy of 90%, demonstrating its effectiveness in distinguishing between eye flu and healthy eyes based on retinal images. However, it doesn't clarify if the validation was performed on an entirely separate dataset from the training data. Ideally, the model should be validated on a completely unseen dataset to assess its true performance on new cases.

Li et al. [21] proposes an Auto-Encoder (AE) based classification method to improve performance. It begins with data normalization to enhance generalization. The core is an AE model with an Encoder that extracts features by compressing input data into latent vectors, and a Decoder that reconstructs the original data from the latent vectors. The training process involves minimizing the reconstruction error between original and reconstructed data. To perform classification, the extracted features from the Encoder are fed into a separate classifier trained to distinguish between categories. An experiment using a conjunctivitis dataset validates this approach. Different loss functions were explored within a regular CNN model, revealing that the choice of loss function can influence classification robustness. The AE-based method outperformed other dimensionality reduction techniques (PCA, NMF) when combined with traditional classifiers. Further investigation into the number of hidden nodes within the latent compressed vector showed a sweet spot between 100 and 200 nodes for optimal classification accuracy on the conjunctivitis dataset. Importantly, the AE-based method demonstrated a significant advantage in reducing the false positive rate compared to traditional classifiers.

Soysa & De Silva [22] tackles eye disease detection through a combination of image processing and deep learning. To address image quality, the system first preprocesses captured images on the server-side by removing noise, enhancing contrast, and resizing them to a uniform dimension. A pre-trained convolutional neural network (CNN) then extracts features from the preprocessed images. To improve feature quality, a G-filter is applied to account for reflection and uneven illumination. Convolutional layers with pooling are used within the CNN to process the image and extract features. These features are then fed into a dense layer for classification into cataract, conjunctivitis, or normal. To prevent the model from overfitting on training data, a portion of the dataset is reserved for validation. Finally, the system integrates the image classification results with user responses from a questionnaire regarding their eye symptoms. A specialist-designed questionnaire gathers user inputs on weighted symptoms, and the final disease assessment is determined by combining the image analysis outcome with the user's symptom data. This approach provides a more comprehensive analysis by combining image processing with user-reported information.

3. MATERIALS AND METHODS

Recent research has explored the application of Artificial Intelligence (AI) and Machine Learning (ML) techniques for automated conjunctivitis detection. These methods offer the potential for faster, more objective, and accessible diagnosis compared to traditional methods. CNNs are a type of neural network specifically designed for processing and analyzing image data. They consist of layers of neurons that are organized in a hierarchical structure. Convolutional layers extract features from the input image, while pooling layers reduce the dimensionality of the feature maps. Fully connected layers then combine the extracted features to produce a classification output.

International Journal of Scientific Research in Engineering and Management (IJSREM)
Volume: 08 Issue: 10 | Oct - 2024 SJIF Rating: 8.448 ISSN: 2582-3930

- **EfficientNet:** A family of CNN architectures that achieve state-of-the-art performance with a minimal increase in computational cost. EfficientNet models are designed using a compound scaling method that uniformly scales the width, depth, and resolution of the network.
- **ResNet:** A deep residual neural network architecture that addresses the problem of vanishing gradients in very deep networks. ResNet introduces residual blocks that skip connections to help the network learn more complex features.
- **VGG-19:** A deep CNN architecture with 19 layers that has been pre-trained on the ImageNet dataset. VGG-19 is known for its simplicity and effectiveness in various image classification tasks.
- **Inception-v3:** A deep CNN architecture that uses a combination of different-sized convolutions to extract features at multiple scales. Inception-v3 is known for its efficiency and accuracy in image classification.

Support Vector Machines (SVMs)

SVMs are a supervised learning algorithm that can be used for classification and regression tasks. SVMs find a hyperplane that separates the data into different classes. The hyperplane was chosen to maximize the margin between the classes.

Deep Neural Networks (DNNs)

DNNs are a type of neural network with multiple hidden layers. DNNs can learn complex patterns and relationships in data. They are often used for tasks such as image classification, natural language processing, and speech recognition.

These models have been successfully applied in various domains, including medical image analysis. In the context of conjunctivitis detection, these models have demonstrated their ability to accurately classify ocular images and distinguish between healthy and diseased eyes.

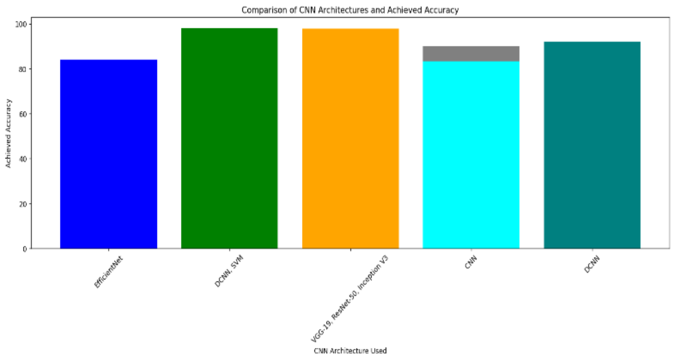

Figure 2: CNN Architecture used

4. RESULT AND DISCUSSION

Datasets: The datasets of our experiments were either publicly available or custom-made by the experimenters themselves. The size of the dataset ranged from 150 to 6000 images. Pictures with normal eyes, conjunctivitis, cataract, among other diseases of the eye are all included in this dataset.

Data Acquisition and Preprocessing: It is of paramount importance to have high-quality diverse datasets, according to all the studies cited above. Resizing, normalization, cropping as well as augmentation are some common pre-processing techniques performed to address few data and generalize the model itself.

Transfer learning: Usually in the form of using pre-trained networks like VGG16, ResNet50, InceptionV3, EfficientNet for feature extraction, saving much training time compared to building a model from scratch.

Model Architectures: The most popular architecture for image classification is Convolutional Neural Networks (CNNs) with features like convolutional and pooling layers for feature extraction and fully connected layers for classification of an image. Other architectures are alternative Autoencoders (AE) for decreasing dimensionality and potentially benefitting classification.

Metrics: Accuracy, precision, recall, F1 score, Area Under Curve (AUC), and confusion matrix have been typically used in the research for performance evaluation.

Overfitting Techniques such as data augmentation and validation sets prevent models from overfitting on training data to ensure generalization to unseen data.

Based on the analysis of the reviewed articles, deep learning approaches show great promise in achieving automated conjunctivitis detection, especially in the application of CNNs. Indeed, reported accuracy ranges between 83.33% and 98%, further boosting the possibility of AI-driven solutions enhancing the efficiency and accuracy of conjunctivitis diagnosis.

However, it must be noted that the performance of such models can be variable based on the above variability. Size and diversity are very key factors in training data because they go a long way in determining the capability of a model to generalize and classify new, unseen data. Specific CNN architectures, hyperparameters, and specific techniques that can be used for data augmentation all play key roles in final accuracy.

From the related work studies analyzed, the highest accuracy obtained was 98% from the use of the combination of DCNN and SVM. This is an indication that under certain scenarios, hybrid approaches do have an advantage by integrating deep learning to more traditional machine learning techniques.

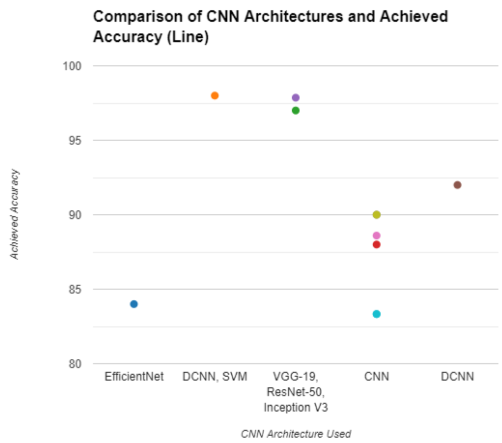

Figure 3: Performance comparison of models

The above results are very promising but do need to be critically noted for its problems and limitations: significant limit associated with the AI-based conjunctivitis detection method is a dependency on high-quality, annotated datasets that require time as well as costly resources for collection and labeling of such datasets. Generalization of the models trained on limited datasets would be limited in their applicability.

5. CONCLUSIONS

The combination of DCNN and SVM is a good example, demonstrated in one of the studied cases, with an accuracy of 98%. This results from the fact that in certain cases, hybrid combinations of deep learning with traditional machine learning methods may indeed work better. However, results depend on the size of the dataset, the methods of augmentation and on the selected CNN architecture. Deep learning methods seem to hold great promise for automatic conjunctivitis detection, but further research is needed to overcome the limitations and ensure reliable and effective deployment in clinical settings. More focus should be given toward developing more efficient acquisition methods for data collection, exploring hybrid approaches, and addressing the issues of interpretability and generalizability of these models.

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