

Convolutional Neural Networks (CNNs) for detection of Eye Diseases in an Effective Manner

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Abstract:

Introduction:

This thesis concentrates on advancing a deep learning system for the precise classification of eye illnesses. Employing the Convolutional Neural Network (CNN) algorithm and Tkinter for GUI, the interface safeguards an intuitive and user-friendly experience. The system effectively identifies various eye conditions, including glaucoma, cataracts, diabetic retinopathy, among others.

Objectives: The main goal of this thesis is to offer a reliable and efficient solution for classifying eye diseases through deep learning techniques by addressing the critical need for timely and accurate diagnosis. The significant contributions of this thesis include: Publication of new datasets beneficial to researchers in the field. Enhancement of a robust segmentation approach, applicable to various retinal conditions, including diabetic retinopathy.

Methods: A supervised learning approach adopted to train the CNN algorithm with an extensive dataset of eye images. The system achieved an impressive accuracy in classifying eye diseases, underscoring its effectiveness in identification and diagnosis. Development of a hybrid characteristic extraction method from segmented objects, utilized by the classifier for detecting glaucoma and other eye diseases.

Results: This system will be able to detect and diagnose the diseases which are related with Eys which will help patients to take care of eyes from further complications. Furthermore, with advancements in portable retinal cameras, integrating the proposed method can facilitate the diagnosis of glaucoma and other eye diseases, thereby enhancing the detection rate, especially in growing nations.

Conclusions: The developed system significantly enhances the accuracy and efficiency of eye disease diagnosis, enabling early detection and treatment. The integration of Tkinter for GUI and the color-blind test feature improves the user experience, making the system more accessible to a broader audience. This thesis underscores the potential of deep learning techniques in medical diagnosis, presenting a valuable tool for healthcare professionals and patients alike.

Keywords: Eye diseases, Deep learning, Convolutional neural network, CNN algorithm, Cataract, glaucoma and other Eye Diseases, Supervised Learning, TKinter, Color blindness, Healthcare.

1. Introduction

Blindness constitutes a substantial global public health concern, impacting millions of individuals. Leading causes include eye conditions like glaucoma, various eye diseases, cataracts, and diabetic retinopathy (DR). Timely and precise diagnosis of these ailments is crucial, yet stimulating due to the intricate and delicate environment of symptoms. Recent advancements in imaging modalities and artificial intelligence (AI) present promising avenues for attractive the accuracy and competence of eye disease diagnosis.

This research centers on the formation of an innovative deep learning-based system designed classifying eye diseases. The system employs a Convolutional Neural Network (CNN) algorithm and incorporates Tkinter for the Graphical User Interface (GUI), offering an intuitive and user-friendly platform for precise and prompt analysis of eye diseases.

The impetus behind this research stems from the substantial impact of eye diseases on public health. The intricate and subtle nature of symptoms in eye diseases, coupled with the time-consuming and costly traditional diagnostic methods, underscores the need for innovative approaches. Deep learning techniques, particularly CNN algorithms, show significant promise in expediting and refining eye disease diagnoses through the analysis of extensive medical imaging data.

This research endeavor's to elevate the standards of eye disease diagnosis and treatment, ultimately contributing to the enhancement of public health. In the realm of modern-day healthcare, advancements in era have paved the way for innovative answers to age-old challenges. One such urgent concern is the accurate and well- timed analysis of eye illnesses, a crucial determinant of preserving vision and enhancing sufferers' standard nicely-being

Conventional strategies of diagnosing eye situations have often been complicated, mistakes-susceptible, and time-extensive, underscoring the want for an extra efficient and specific method. With the arrival of deep learning strategies, my task aims to convert the landscape of ocular healthcare via introducing a clever and automated gadget. This gadget harnesses the skills of deep learning algorithms to investigate complicated visible information, especially fundus pictures, and accurately come across a number of eye disorders.

2. Objectives

The primary aim of this thesis is to devise a sophisticated deep learning-based framework dedicated to the precise and efficient classification of eye diseases.

The specific objectives delineated for the study are as follows:

1. Conducting the comprehensive collection and preprocessing of an extensive dataset comprising medical images to serve as the foundational training data for the Convolutional Neural Network (CNN) model.
2. Formulating and implementing a state-of-the-art CNN model tailored for the nuanced classification of diverse types of eye diseases.
3. Undertaking the training of the CNN model utilizing the meticulously assembled dataset and subsequently evaluating its performance through rigorous assessments.
4. Crafting an intuitive and user-friendly Graphical User Interface (GUI) utilizing the tkinter

framework, with a particular focus on enhancing accessibility for both healthcare professionals and patients.

5. Integrating a feature allowing users to partake in a color blindness test through a dedicated portal on a new forum website.
6. Validating the performance of the developed system by employing a spectrum of evaluation metrics, thereby ensuring robustness and reliability in its diagnostic capabilities.
7. Conducting a comparative analysis to assess the performance of the developed system against existing methodologies for eye disease diagnosis, with the objective of discerning advancements and contributions in the field.

The successful accomplishment of these objectives is anticipated to significantly contribute to the amelioration of the challenges associated with the accurate and efficient diagnosis of eye diseases. This, in turn, is poised to elevate the standard of healthcare provision and, by extension, contribute positively to public health outcomes.

3. Methods

The operational model of this system encompasses several essential components:

Image Processing with Data Analysis: Employing advanced image processing and analysis techniques, such as machine learning and computer vision, is crucial for accurate disease classification and detection. These technologies can assist healthcare providers in making more precise diagnoses and treatment decisions, potentially leading to better patient outcomes.

Database: A robust and secure patient database is essential for storing and managing patient information. It not only includes medical history and diagnostic images but also aids in tracking changes in a patient's condition over time. This data-driven approach can help in tailoring treatment plans and monitoring the effectiveness of interventions.

User Interface: A user-friendly interface, whether web-based or mobile-based, is vital for patient engagement and accessibility. It allows patients to easily provide information and upload diagnostic images, promoting active participation in their healthcare. Moreover, a well-designed interface can improve the overall user experience.

Disease Information: Providing accurate and up-to-date information on various eye diseases is critical for educating both healthcare providers and patients. This knowledge empowers patients to understand their conditions better and make informed decisions about their treatment options. It also helps healthcare providers stay updated with the latest developments in the field.

Eye Care Information: Prevention is often better than cure. Offering information on maintaining eye health and the importance of regular eye exams can help prevent eye diseases or detect them at an earlier, more manageable stage. This educational aspect of the system promotes proactive healthcare and wellness.

Communication Interface: Facilitating communication between patients and healthcare providers is essential for coordinated care. The ability to exchange information, test results, and treatment

recommendations enhances collaboration and ensures that all parties involved are on the same page regarding the patient's condition and treatment plan.

Testing and Validation: Prior to deployment, the system undergoes rigorous testing and validation processes. This ensures its accuracy, reliability, and user-friendly nature, addressing any potential issues or discrepancies.

Deployment: Healthcare providers can then utilize the system for diagnosing and treating patients with various eye diseases, leveraging the integrated functionalities.

In summary, the operational model of this system integrates advanced image processing, a comprehensive patient database, user-friendly interfaces, accurate disease and eye care information, communication interfaces, and thorough testing and validation processes. This holistic approach ensures the system's effectiveness, reliability, and suitability for deployment in healthcare settings.

System Architecture

The system architecture involves the integration of distinct modules, each dedicated to specific functionalities:

The system architecture is modular, comprising distinct modules tailored for specific functions. These modules collectively contribute to the overall functionality of the system, encompassing image processing, database management, user interaction, information dissemination, preventive care, communication, maintenance, and data security.

During training, the CNN adjusts the weights of its filters and fully connected layers through backpropagation.

The optimization of CNNs is a critical step in training deep learning models for tasks like image classification. It starts with the selection of an appropriate loss function, often the cross-entropy loss, which quantifies the difference between the predicted probabilities generated by the model and the actual class labels of the training data.

During training, the CNN performs a forward pass to make predictions on the training data. The error or loss is then calculated using the chosen loss function. The key to optimizing the network lies in the subsequent backward pass, known as backpropagation.

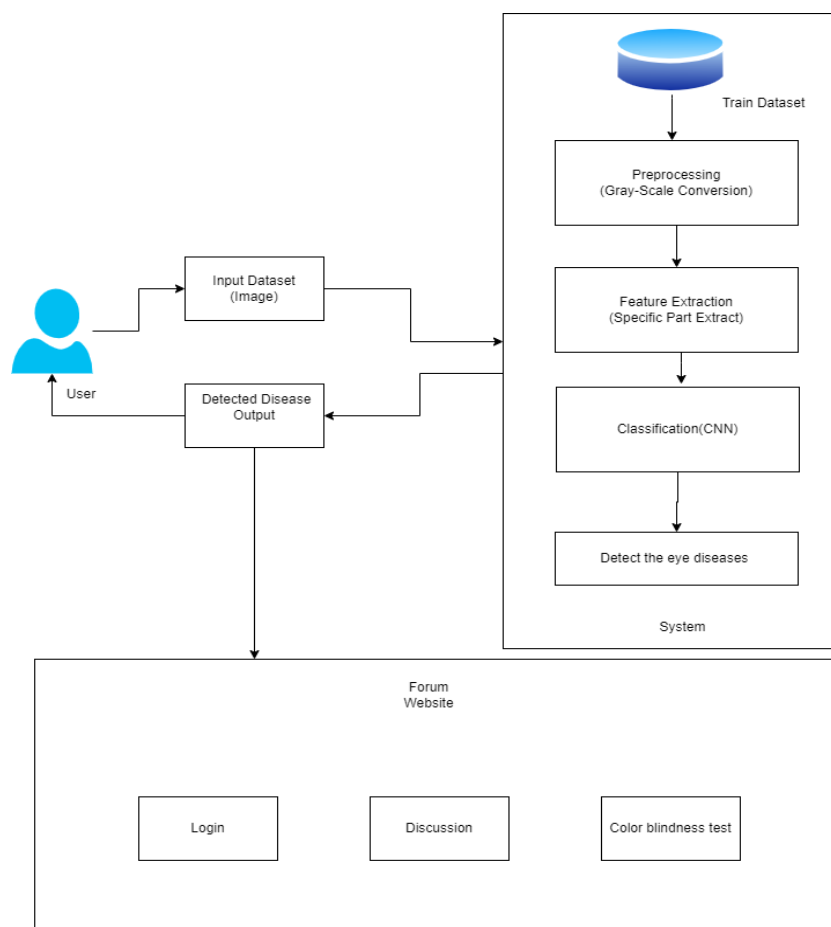


Figure 1: System Architecture

Backpropagation computes the gradients of the loss function with respect to the model's weights and biases, effectively quantifying how much each weight contributed to the overall error.

Convolutional Neural Network (CNN) Operations:

Convolution Operation:

The mathematical equation for a 2D convolution operation is typically represented as: $\text{Output}[i, j] = \sum (\text{Filter} * \text{Input}[i: i+H, j: j+W]) + \text{Bias}$ Where Filter is the convolutional filter, Input is the input image,

ReLU Activation:

It is a activation function is often used after convolution to introduce non-linearity.

Mathematically, ReLU is defined as: $\text{ReLU}(c) = \text{maximum}(0, c)$

Max-Pooling:

Purpose: Reduces spatial dimensions and retains important features.

Mathematically, within a sliding window.

Model Training:

Loss Function:

In training the CNN, a loss function (typically categorical cross-entropy for classification tasks) is used to measure the error between predicted and actual labels.

For binary classification, the mathematical representation of binary cross-entropy loss can be:

BinaryCrossEntropyLoss = $-(y * \log(y_hat) + (1 - y) * \log(1 - y_hat))$ Where y is the true label, and y_hat is the predicted probability.

Gradient Descent:

Optimization algorithms like stochastic gradient descent (SGD) are used to update model weights based on gradients.

Mathematically, the weight update step can be represented as: $Weight = Weight - LearningRate * Gradient$

Gradient

Model Evaluation:

Metrics:

Metrics like accuracy, precision, recall, F1-score, and ROC AUC are calculated using mathematical formulas based on true positive (TP), true negative (TN), false positive (FP), and false negative (FN) values.

Confusion Matrix:

A confusion matrix is often used to compute the values needed for metrics.

For instance, precision and recall can be calculated using: $Precision = TP / (TP + FP)$

$Recall = TP / (TP + FN)$.

4. Results

It's commendable that the iHealth website not only offers color blindness tests but also provides valuable to enhance their understanding of their needs.

The Ishihara color blindness test, developed by Dr. Shinobu Ishihara in 1917, is a widely used method for assessing color vision deficiency. It consists of plates with colored dots arranged to form numbers or shapes that individuals with normal color vision can easily identify. However, those with color vision deficiency may struggle to see or correctly identify these patterns.

During the test, individuals are presented with these plates and asked to identify the numbers or shapes they perceive.

The world faces a staggering challenge in the form of vision impairment, with the Lancet Global Health Commission report painting a grim picture. An estimated 596 million people struggle with distance vision impairment, while 510 million grapple with uncorrected near vision issues. This translates to countless individuals facing difficulties in daily life, from navigation and reading to social interaction and employment.

The factors fueling this global crisis are diverse and complex. An aging population naturally sees an increase in age-related eye conditions like cataracts and macular degeneration. Comorbidities such as diabetes also play a significant role, while the modern world's increased exposure to blue light from electronic devices adds another layer to the problem.

However, the situation is particularly dire in developing countries like India. This nation alone counts 62 million individuals with visual impairment, a staggering 8 million of whom are blind. The tragedy lies in the preventable nature of much of this vision loss. The National Blindness and Visual

Impairment Survey reveals that cataracts, a treatable condition requiring a relatively simple surgical procedure, are responsible for a concerning 66.2% of blindness in individuals over 50.

Despite the availability of accessible and effective surgery to replace the clouded lens with an artificial one, barriers to care create a heartbreaking scenario. Rural and semi-rural areas often lack adequate access to skilled ophthalmologists and equipped healthcare facilities. Financial constraints deter many from seeking treatment, while fear of surgery and a lack of awareness about available solutions further exacerbate the problem.

Strengthening healthcare infrastructure, particularly in underserved areas, is crucial.

Public awareness campaigns can dispel myths and misconceptions surrounding eye health and treatment options. Affordability and accessibility of ophthalmic care must be prioritized, while fostering trust in medical professionals through community engagement can encourage timely interventions.

Ultimately, tackling the global vision crisis requires a concerted effort from governments, healthcare providers, NGOs, and communities. By addressing the social, economic, and geographical barriers to care, we can move towards a future where sight is not a privilege but a right, empowering individuals to lead fulfilling and productive lives.

This emphasizes the need for proactive measures, including education, early detection, and accessible treatment options.

Accuracy v/s Epoch

Accurately diagnosing glaucoma hinges on the ability to decipher subtle clues within retinal images. One such crucial task is determining the laterality of the eye, whether it's a right eye or a left eye. This seemingly simple question holds immense significance for machine learning models trained to detect glaucoma. Why? Because the distribution of blood vessels and other key features differs between the two sides of the eye.

Here's where the cleverness kicks in:

Simple case: If the disc itself is located to the left of the original image, it inherently signifies a left eye. Conversely, a disc positioned to the right implies a right eye. This straightforward approach leverages the disc's natural asymmetry to provide immediate laterality information.

Ambiguous cases: For images where the disc's position isn't conclusive, the algorithm resorts to a more nuanced analysis. It compares the vessel areas in the left and right halves around the disc.

By combining these two complementary strategies, Algorithm offers a versatile

and reliable approach for deciphering eye laterality. This seemingly simple step plays a critical role in training machine learning models for glaucoma detection. Knowing whether an image is from a left or right eye allows the model to interpret features and patterns more accurately, ultimately leading to improved diagnostics and potential.

The accuracy and loss plots are crucial visualizations in monitoring the training process of a machine learning model. Accuracy represents the percentage of correctly predicted instances out of the total

instances. The higher the accuracy, the better the model's performance. One epoch is a complete pass through the entire training dataset. The x-axis shows the number of epochs, and the y-axis shows the accuracy. An increasing accuracy curve suggests that the model is improving its predictive capability as training progresses. However, fluctuations or plateaus may also occur, indicating potential issues like overfitting or convergence. Loss: This metric quantifies how well the model's predictions match the actual values. It represents the error between predicted and true values.

Epochs: Similar to the accuracy plot, the x-axis represents the number of epochs, and the y-axis represents the loss.

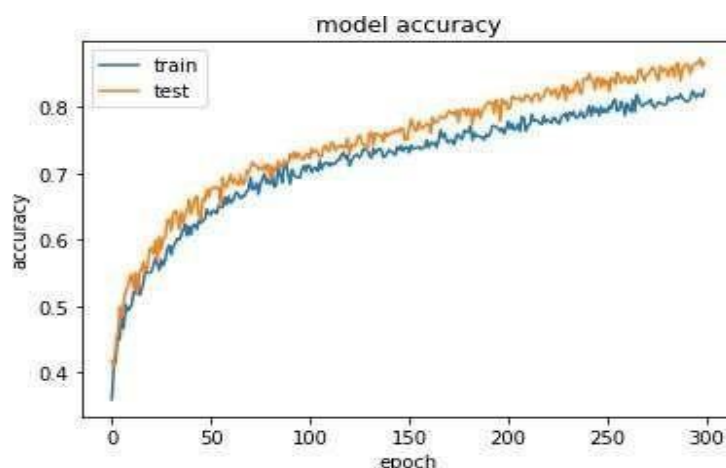


Figure 2: Accuracy v/s Epoch (300)

Interpretation: The goal is to minimize the loss. A decreasing loss curve indicates that the model is becoming more accurate in its predictions. However, spikes or increases in loss may suggest issues like model instability or overfitting. For both plots, it's essential to strike a balance between high accuracy and low loss. Overly focusing on accuracy might lead to overfitting, where the model memorizes the training data but fails to generalize well to new data. Monitoring the loss helps ensure that the model is improving its generalization performance.

5. Discussion

In the field of reliable approaches were developed in the thesis. Instead of creating a single black-box deep learning model, various models were developed to segment objects from retinal images. Once segmented, features were related to glaucoma.

The thesis's contribution includes the development of multiple deep learning models that demonstrated outstanding performance across diverse datasets. A comprehensive literature review was conducted, providing insight into glaucoma and image processing. Various techniques for glaucoma detection were developed, focusing on fundus images. While optic disc extraction achieved high accuracy, cup extraction and vessel segmentation presented challenges that need further attention.

The review considered the increasing availability of datasets for glaucoma detection, with emerging deep learning techniques showing promise. Transfer learning was identified as a valuable concept to enhance deep learning algorithms' performance. The thesis sets the foundation for

building a platform assisting ophthalmologists and optometrists in making informed decisions in glaucoma diagnosis.

Overall, the thesis contributes to advancing of deep learning in eye disease classification, with potential implications for improving early detection and patient outcomes in the field of ophthalmology.

This study ventured into the fascinating realm of disc delineation, investigating the nuanced discrepancies in how ophthalmic professionals mark. The primary focus hinged on evaluating the level of agreement and precision exhibited by optometrists when tasked with tracing the disc boundaries. To facilitate this intricate examination, a bespoke web portal was meticulously crafted, specifically designed for accurate disc annotation.

The findings revealed a noteworthy contrast: while optometrists displayed remarkable consistency in pinpointing the disc's general location, pinpointing its precise edges proved to be a more formidable challenge. Intriguingly, the study unraveled a mosaic of variations in their ability to discern the intricate disc boundary across different image regions. These discrepancies were further unmasked by the distinct levels of difficulty encountered while differentiating the disc from the peripapillary atrophy (PPA) zone.

Several factors emerged as key contributors to this observed variability. Unclear disc margins, the tendency to rely on the bends of blood vessels as boundary markers, and potential calibration inconsistencies were identified as culprits behind the observed deviations. Interestingly, the research team implemented an ellipse-fitting technique as a potential equalizer, demonstrating its effectiveness in mitigating misalignments and bolstering agreement and precision, particularly for specific challenging images.

Low resolution and obscured disc visibility in some images cast a shadow on the optometrists' ability to accurately trace the boundaries. Notably, OD1, the first optometrist involved in the study, consistently outperformed OD2, as evidenced by higher Dice coefficients (DC) and lower average boundary distances.

These insightful findings served as a springboard for the development of a robust deep learning model capable of segmenting the disc with exceptional precision. The generated data, a testament to the collaborative spirit of the research team, has been generously made available for further exploration and advancement in this critical area of retinal image analysis.

Transfer learning: Levering pre-trained knowledge from a well-honed network, the model swiftly grasped the intricacies of retinal anatomy, accelerating its learning process.

Image augmentation: Mimicking real-world variations encountered in the diverse image database, the model was trained on artificially expanded data, bolstering its generalizability and resilience to noise.

Custom loss function: Tailoring the evaluation metric to prioritize accurate disc boundaries, the model honed its focus on capturing the subtle nuances of the optic disc margin.

This potent combination propelled the model to new heights of performance, surpassing the achievements of existing methodologies. With an astonishing average accuracy of 99.78%, the model

showcased near-perfect precision in delineating the disc. The Dice coefficient of 94.73% and sensitivity of 96.26% highlighted its remarkable ability to capture even the subtlest contours of the disc margin. Furthermore, the Intersection over Union (IoU) score of 90.13% underscored the model's proficiency in differentiating the disc from its neighboring areas.

To foster further advancements in disc segmentation research, a novel dataset dubbed ORDS was meticulously curated. This rich collection of diverse images, meticulously annotated with precise disc boundaries, serves seeking to develop and refine their own algorithms.

Next, the attention shifted to the enigmatic inner sanctum of the disc. Utilizing the ROI identified by the previously-developed disc model, another model was architected to tackle the challenge of cup segmentation. Embracing the principle of efficiency, the team opted to leverage the pre-trained model employed for vessel segmentation in the preceding chapter. This strategic reuse of existing knowledge streamlined the development process and capitalized on the model's pre-existing understanding of retinal features.

The development of these robust deep learning models marks a significant leap forward in the realm of automated analysis. By accurately delineating both the disc and cup, these tools hold immense potential in aiding clinicians in diagnosing and managing glaucoma, a sight-threatening disease. Moreover, the publicly available ORDS dataset attests as a testament to the researchers' commitment to furthering this field through collaborative efforts. As exploration progresses, we can anticipate witnessing even greater strides in precision and efficiency, ultimately translating into improved patient care and earlier disease detection.

Based on current information and available medications, there are steps we can take now to significantly reduce the burden of vision impairment in the coming years. To ensure that the public, especially low-income and at-risk populations, can find and access convenient, high-quality eye care, efforts are needed to create an impression of eye care facilities outside of hospitals. Eye care providers and ophthalmologists in the workplace. There are also steps individuals and communities can take to create social contexts that effectively and passively promote healthy eye behaviours. However, current information alone is not sufficient to ensure ideal eye and vision health. In fact, there are no long-term exploration and research projects to identify the most at-risk populations, their associated risk factors and protective components, and an open wellness framework model that can expand access to cost-effective medications, effective health care, and medical support.

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