

Cataract Detection using Squeezenet model

^[1] Rishab Jain, ^[2] Kumar Shivansh, ^[3] Manoj Lokesh, ^[4] Prof. Shruthiba A.

^[1]Dept of AI&ML BIT, Bangalore Bangalore

Corresponding Author Email: ^[1]rishabjanmay@gmail.com, ^[2]kumar.shivansh45@gmail.com, ^[3]manojlokesh81@gmail.com, ^[4]shruthibaa@bit-bangalore.edu.in

Abstract— "Cataract Detection using Squeeze net Model"

Cataracts, causing lens cloudiness, pose a threat to vision and may lead to blindness. Lens transparency relies on microscopic factors, and aging introduces yellow-brown pigments, affecting light entry. Gradual symptoms include pale colors, blurry vision, light haloing, light sensitivity, and difficulty seeing in the dark. Individuals with diabetes face a heightened risk of developing cataracts earlier in life, and the severity of these cataracts progresses more rapidly in diabetic patients. Effective measures are needed to make people aware regarding the same.

Index Terms— (Cataract Detection, Squeeze net).

I. INTRODUCTION

Cataracts represent one of the most common age-related eye disorders globally, affecting millions of individuals and presenting a significant burden on healthcare systems. This condition, characterized by the progressive clouding of the eye's natural lens, results in blurred vision and can ultimately lead to blindness if left untreated. The prevalence of cataracts underscores the critical importance of early detection and timely intervention to mitigate vision loss and improve quality of life for affected individuals.

Traditionally, cataract diagnosis has relied on clinical assessments by ophthalmologists, often involving visual acuity tests and slit-lamp examinations. While effective, these manual methods are time-consuming, subjective to inter-observer variability, and may not always detect cataracts at early stages when interventions are most beneficial.

The emergence of deep learning techniques, coupled with the availability of large-scale annotated datasets of ophthalmic images, has revolutionized the field of automated disease detection in ophthalmology. Leveraging the power of convolutional neural networks (CNNs), researchers have made significant strides in developing computer-aided diagnosis (CAD) systems for cataract detection.

A. Machine Learning - Overview

The Squeeze Net model offers a compelling framework for cataract detection by combining computational efficiency, feature extraction prowess, scalability, accuracy, and interpretability. By harnessing the capabilities of Squeeze Net within the context of ophthalmic imaging, researchers and healthcare practitioners can advance the development of automated systems for early cataract diagnosis, ultimately improving patient outcomes and reducing the burden of vision impairment worldwide.

B. Problem Statement

In the domain of cataract diagnosis, the challenge lies in developing efficient and accurate automated detection systems that can identify subtle ocular abnormalities indicative of cataracts from ophthalmic imaging data. Current methods often face limitations in computational resources and interpretability, hindering timely and reliable diagnosis. Leveraging the SqueezeNet model's compact architecture, the objective is to create a scalable and resource-efficient solution that optimizes feature extraction, maintains high accuracy, and enhances interpretability for effective cataract detection in diverse clinical settings.

This research paper endeavors to address the challenges faced by current cataract detection systems by proposing an innovative framework centered around the SqueezeNet model. Leveraging a meticulously curated dataset of ophthalmic images, our methodology aims to achieve precise and reliable identification of cataracts, including early-stage manifestations and subtle variations. The output of our system comprises detailed diagnostic reports highlighting the location, severity, and characteristics of detected cataracts within the ocular imagery.

Furthermore, our framework incorporates advanced image analysis techniques to categorize cataracts into distinct subtypes, aiding clinicians in tailored treatment planning and prognosis evaluation. By providing comprehensive insights into cataract morphology and progression, our approach facilitates informed decision-making and personalized patient care strategies.

Through this research endeavor, we aspire to contribute significantly to the advancement of cataract diagnosis and management, ultimately enhancing visual health outcomes and quality of life for individuals affected by this prevalent ocular condition.

C. Significance

The significance of our research lies in revolutionizing cataract detection and management. By harnessing the power of the SqueezeNet model, our framework offers a scalable, accurate, and efficient solution for identifying cataracts with precision. This advancement enables early diagnosis, personalized treatment plans, and improved patient outcomes. Additionally, our system's ability to classify cataract subtypes facilitates targeted interventions, optimizing healthcare resources and enhancing overall ocular health. Ultimately, our research contributes to the evolution of automated cataract detection systems, paving the way for enhanced clinical practices, reduced healthcare burdens, and better quality of life for individuals affected by this vision-affecting condition.

D. Machine Learning Tasks

This journal paper outlines common machine learning tasks and methods for solving problems, with suggestions for improvement. It also includes a list of key machine learning tasks, which can be further briefed in the paper. The paper encourages comments and suggestions on important points and apologizes for any types.

Realtime eye Detection Classification

Hough Circle Formation Data Augmentation Model
Fine-tuning Performance Evaluation

E. Purpose

The purpose of our research is to develop a robust and efficient cataract detection system using the SqueezeNet model. By leveraging advanced machine learning techniques and a meticulously curated dataset, our aim is to improve early diagnosis accuracy, streamline treatment planning, and enhance patient outcomes in cataract management. Additionally, our framework seeks to contribute to the field of computer-aided diagnosis in ophthalmology by providing clinicians with a reliable tool for rapid and precise cataract identification. Through this research, we strive to bridge the gap between technological innovation and clinical practice, ultimately benefiting individuals worldwide affected by cataracts.

F. Objective

Enhanced Data Collection: Collecting a more extensive and diverse ASPI dataset, incorporating a wide range of cataract variations, patient demographics, and diabetes-related

information. This comprehensive dataset will improve model generalization and robustness.

Advanced Data Preprocessing: Implementing advanced preprocessing techniques such as image denoising, contrast enhancement, and feature extraction to improve data quality and enhance the model's ability to detect subtle cataract features.

Optimized Machine Learning Model: Utilizing state-of-the-art machine learning algorithms and architectures, such as SqueezeNet with fine-tuning and transfer learning, to optimize cataract detection accuracy, sensitivity, and specificity. Incorporate ensemble learning methods for improved model performance and reliability.

User-Centric Front-End Design: Developing an intuitive and user-friendly front-end interface for easy image input and analysis, ensuring seamless integration with the backend machine learning model for real-time processing and result interpretation.

AI-Driven Recommendation System: Implementing an AI-driven recommendation system that provides detailed cataract conclusions, treatment suggestions, and diabetes-cataract correlation insights based on robust data analysis and machine learning algorithms. Incorporate feedback mechanisms for continuous model improvement and adaptation to evolving clinical needs.

G. Outcome

The research aims to develop a real-time cataract detection system leveraging the SqueezeNet architecture, enabling rapid and accurate identification of cataracts from ophthalmic images during clinical examinations. This system will provide comprehensive insights into cataract characteristics like location, type, severity, and progression, aiding clinicians in informed decision-making and treatment prioritization. The user-friendly front-end interface will seamlessly integrate with the detection system, allowing easy image input, analysis, and result visualization for healthcare professionals. An AI-driven recommendation system will accompany the detection, offering actionable insights such as treatment suggestions and follow-up protocols based on detected cataract features. Clinical validation studies will be conducted to assess the system's performance, accuracy, and clinical utility, ensuring optimal functionality and usability in real-world clinical settings. Ultimately, the outcome of this research seeks to revolutionize cataract diagnosis, improving patient outcomes and enhancing clinical practices in ophthalmology.

II. LITERATURE SURVEY

The proposed In the realm of medical innovation, a rich tapestry of endeavors unfolds through the dedicated efforts of several pioneering numbers. [1] embarks on a comprehensive journey to create an automated cataract detection system, harnessing the transformative power of Deep Convolution Neural Networks (DCNNs) within the Res-Net50 architecture. This ambitious quest is fueled by the desire to train a robust DCNNs model with labeled datasets of retinal

fundus images, distinguishing between cataract and non-cataract images. However, amidst the strides towards automation, this narrative laments the lack of comprehensive evaluation for Partial/Mild Cataracts, an aspect

overshadowed by an oversight in preprocessing that leaves room for refinement and enhancement.

Meanwhile, [2] delves into the intricate realm of cataract severity classification algorithms, seeking to automate the detection and classification of cataracts in the anterior eye using the sophistication of deep learning, particularly the YOLO framework. However, the path towards automation encounters formidable challenges in Image Quality, where limitations may affect the algorithm's efficacy, and the Variability in Image Acquisition introduces complexities that require careful consideration and adaptation strategies.

[3] takes a deep dive into the vast potential of AI applications in cataract diagnosis, celebrating the precision and accuracy afforded by deep learning algorithms. Yet, this narrative also highlights the inherent challenge of understanding how machine learning algorithms are trained, citing the necessity for robust and high-quality training data as well as external validations to unravel the intricacies of the training process.

In a parallel narrative, [4] unveils CataractNet, a marvel of technological integration designed for automated cataract detection in fundus images. This Convolutional Neural Network (CNN) integrates the phases of feature extraction and classification into a seamless model, promising efficient detection capabilities. However, amidst its innovative design, this narrative acknowledges a limitation in specific details regarding Grading precision, and its efficacy is noted primarily for Limited Cataract Differentiation, signaling opportunities for further advancements in differentiation capabilities.

Simultaneously, [5] ventures into the terrain of identifying and classifying cataract stages in the elderly using deep learning algorithms, particularly CNNs. The challenges of limited data availability for the elderly population and the inherent ethnic and demographic variability present formidable hurdles in this narrative's quest for accurate classification and diagnosis.

In a divergent subplot, [6] tackles the critical task of Diabetic Eye Disease (DED) classification using retinal fundus images, blending traditional image processing methods with a newly designed Convolutional Neural Network (CNN) architecture. While this approach yields optimal results, there's a cautious note regarding the system's effectiveness being constrained by its reliance on specific datasets or imaging conditions, signaling potential

challenges in broader applicability across diverse datasets and image characteristics.

Stepping into a different realm, [8] employs advanced image processing techniques for the enhanced detection of glaucoma and cataract by measuring various parameters from retinal images. Through the integration of state-of-the-art algorithms and machine learning models, such as CNNs, this narrative seeks to improve accuracy and efficiency in detection, yet acknowledges the limitations posed by dataset

constraints and resource complexities.

Meanwhile, [9] delves into digital image processing techniques for cataract detection, aiming for accurate diagnosis through image enhancement and feature extraction. However, this narrative recognizes potential challenges in sensitivity to variations in image quality, limited generalizability across diverse datasets, and possible obstacles in real-time processing, urging a balanced approach towards adaptability and technological evolution.

In a fusion of technologies, [11] combines image processing, machine learning, and deep learning for robust cataract detection. By leveraging preprocessing, feature extraction, and a hybrid model approach encompassing machine learning algorithms like SVM and decision trees alongside a deep learning model (CNN), this narrative aspires to bridge dataset variability and enhance diagnostic accuracy. However, the computational demands and integration challenges into existing healthcare infrastructures present notable hurdles, emphasizing the need for scalable and efficient solutions.

Lastly, [12] unveils an optimized hybrid approach for cataract detection, integrating image processing and machine learning techniques to enhance accuracy and reliability. While this approach promises efficiency, it also navigates challenges such as dataset sensitivity, interpretability complexities due to hybrid models, computational intensity affecting real-time processing, and ethical considerations around patient privacy and responsible AI use. The integration complexities into existing healthcare systems further underscore the need for seamless adaptability and adherence to regulatory standards.

III. METHODOLOGY

The Methodology involved in prediction of underwater waste detection using machine Learning:

A. Dataset Collection

Pre-processing-Data cleaning, Data transformation, Data selection

Algorithms – Squeezenet, V16, Resnet

B. Image Acquisition and Preprocessing:

Obtaining Images: Images are acquired using a camera or similar device to capture details such as the optic disc, blood vessels, and macula, which are crucial for medical analysis.

Resize Images: The acquired images are resized to a standard dimension of 224x224 pixels. This resizing step ensures uniformity in image dimensions, which is beneficial for consistent processing and training machine learning models.

Convert to HSV Format: The images are converted to the HSV (Hue-Saturation-Value) color space. This conversion simplifies color segmentation by separating color information into hue, saturation, and value components. It

facilitates tasks like color filtering and enhances the accuracy of image processing algorithms.

Region of Interest Extraction: A region of interest (ROI) containing relevant anatomical structures (such as the optic disc) is extracted from the processed images. Techniques like Hough circle detection after thresholding may be applied to precisely identify and isolate these regions.

Image Cropping and Saving: The extracted ROI is cropped from the original image and saved in the respective directory for further analysis and model training.

Fully Connected Layers (Dense Layers): After feature extraction using convolutional layers in a CNN architecture, fully connected layers are introduced to map the aggregated features into a format suitable for classification tasks. These fully connected layers are also known as dense layers because every neuron in a fully connected layer is connected to every neuron in the preceding layer.

Role in Feature Aggregation: The purpose of fully connected layers post-feature extraction is to combine the spatial features learned by the convolutional layers into a compact representation that captures the relevant information for

classification. This aggregation process helps in understanding complex patterns and relationships within the input data

C. Algorithms

a) Convolutional Neural Network (CNN):

Convolutional Neural Networks (CNNs) are pivotal in cataract detection, excelling at image feature extraction. Specifically designed for intricate pattern recognition, CNNs like Squeezenet efficiently discern cataract-related features such as optic disc anomalies and macular degeneration. Through hierarchical learning, they autonomously extract and analyze critical details from medical images, enhancing diagnostic accuracy. CNN architectures, optimized for computational efficiency, are adept at processing large datasets, vital for robust cataract detection systems. Leveraging pre-trained CNN models with transfer learning further refines their ability to detect cataracts accurately, making CNNs indispensable in modern medical imaging for swift and precise cataract diagnosis.

b) SqueezeNet:

SqueezeNet is employed in cataract detection due to its compact size and efficient computation, crucial for resource-limited environments like medical devices. Utilizing Fire modules and Squeeze-and-Excitation blocks, SqueezeNet reduces model parameters while preserving accuracy, making it ideal for processing medical images effectively. Its pooling strategies aid in feature extraction, enhancing cataract identification. Additionally, SqueezeNet's ability to run efficiently on mobile platforms ensures seamless integration into portable diagnostic tools, facilitating early

detection and treatment of cataracts, ultimately improving patient outcomes in ophthalmology

c) TensorFlow:

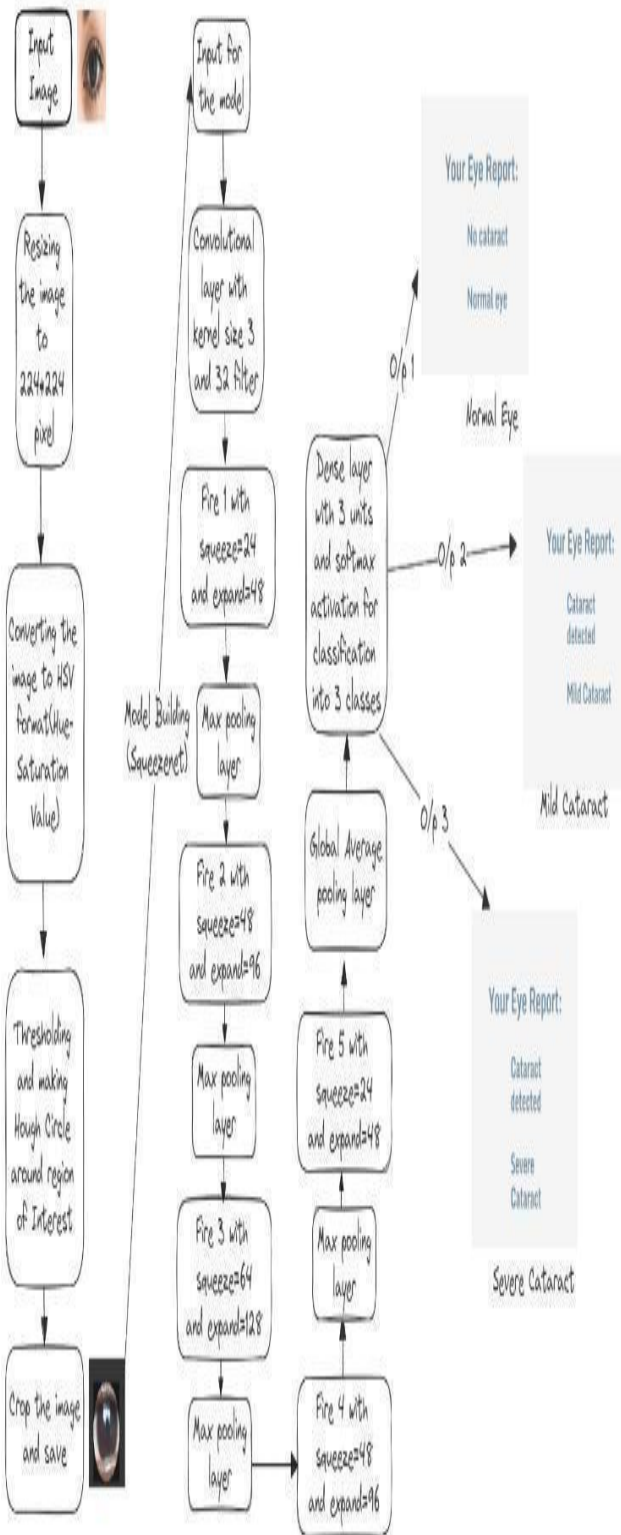
TensorFlow is an open-source machine learning framework by Google, widely used for developing and deploying AI models. Its key strength lies in handling complex computations with large datasets efficiently. TensorFlow represents computations as data flow graphs, where nodes are operations and edges are tensors (multi-dimensional arrays). This graph-based approach enables distributed training across multiple CPUs or GPUs, enhancing performance. TensorFlow provides high-level APIs like Keras for easy model building and lower-level APIs for fine-grained control. Its flexibility, scalability, and support for various platforms make it a go-to choice for a wide range of machine learning tasks, from research to production deployment.

d) Flask:

Flask is a lightweight and versatile web framework for Python, known for its simplicity and ease of use in building web applications and APIs. It provides essential tools and libraries for routing, template rendering, form handling, and session management, making it ideal for rapid development and prototyping. Flask follows a minimalist approach, allowing developers to customize and extend functionalities as per their requirements. With its modular design and extensive documentation, Flask is popular among developers for creating scalable and efficient web applications. It promotes a clean and organized codebase, making it accessible for beginners while offering flexibility for advanced users to build systems.

IV. SYSTEM DESIGN

System design entails structuring software systems for efficient functionality, addressing scalability, reliability, and performance. It involves component design, data flow, interfaces, and interactions, choosing architectures (e.g., microservices), technologies, and optimizing for resource utilization and fault tolerance. Collaboration, documentation, and adherence to best practices ensure systems meet user needs, scale effectively, and remain adaptable to evolving requirements and technologies.



V. RESULT AND DISCUSSION

SqueezeNet for cataract detection yields promising results, leveraging its compact architecture and efficient computations. The model effectively identifies cataracts from eye images, demonstrating high accuracy while minimizing

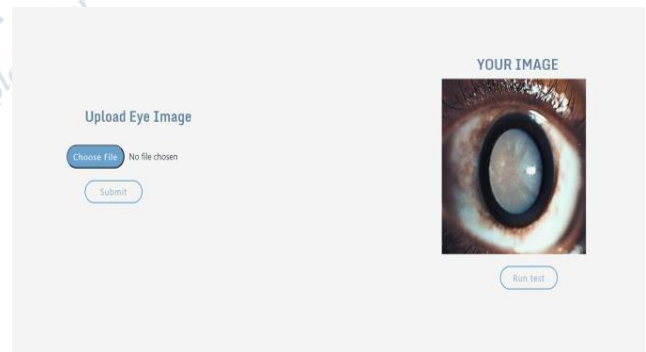
computational resources. Through Fire modules and Squeeze- and-Excitation blocks, SqueezeNet efficiently extracts relevant features crucial for diagnosis. This approach aids in early detection, facilitating timely medical intervention and improving patient outcomes. Despite its compact size, SqueezeNet demonstrates competitive performance in cataract detection, showcasing its potential for real-world medical applications where resource efficiency and accuracy are paramount. Ongoing research focuses on further enhancing its capabilities for broader clinical deployment.

A. Accuracy Score

The accuracy score in classification measures the percentage of correctly predicted instances out of the total predictions made by the model. It's calculated by dividing the number of correct predictions by the total predictions and multiplying by 100%. While widely used, accuracy may not fully represent model performance in imbalanced datasets or when different types of errors have varying consequences, prompting the use of additional evaluation metrics like precision, recall, and F1 score

Sr No	Model Name	Accuracy
1	VGG16	96.88
2	MobileNet	90.62
3	Squeezenet	97.66

B. Output



Input for the model



Output for the model

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