Introduction

Glaucoma, often called the "silent thief of sight," is a progressive eye disease that can lead to irreversible damage to the optic nerve, resulting in vision loss. It affects over 76 million people worldwide and is one of the leading causes of blindness. The main risk factor for glaucoma is high intraocular pressure (IOP), but even people with normal IOP can develop the disease. Because glaucoma often has no symptoms in its early stages, many patients don't realize they have it until significant damage has already occurred. Timely diagnosis and treatment are crucial for preventing further vision loss.

Traditional methods for diagnosing glaucoma are effective but can be time-consuming, resource-heavy, and prone to human error. This highlights the need for advanced technologies that can help with early detection.

In our approach, we use deep learning techniques to improve the accuracy and efficiency of glaucoma diagnosis. Specifically, we utilize Inception V3 and ResNet-150 models to classify retinal images as healthy or glaucomatous. Inception V3 is good at spotting complex patterns, while ResNet-150 helps with deeper networks by addressing the issue of vanishing gradients. By training these models on retinal images, we aim to classify eyes with high accuracy.

We also use a multiclass UNet model to segment the optic disk, a key area for evaluating damage from glaucoma. This segmentation helps us identify changes in the optic nerve head, allowing for more detailed analysis of the disease's progression. To strengthen our models, we enhance our dataset using Roboflow, a platform that provides advanced image preprocessing and augmentation. This step helps increase the variety in our dataset, improving the models' ability to generalize.

Looking to the future, this project has great potential. By integrating ongoing data and real-time monitoring, we could create models that not only diagnose glaucoma but also track its progression over time. The social impact of this project is significant, as it aims to provide an AI-driven solution for diagnosing glaucoma, especially in underserved communities with limited healthcare access. This technology can make high-quality diagnostic tools available to many, helping millions preserve their sight through timely intervention. By raising awareness about the risks of glaucoma and encouraging early screenings, our work seeks to promote a proactive approach to eye health, greatly improving the quality of life for those at risk.

Literature Survey

Xue et al.[1] proposed a multi-feature deep learning (MFDL) system combining intraocular pressure (IOP), color fundus photographs (CFP), and visual field (VF) data. The system, trained on 6,131 samples, achieved 0.842 accuracy, outperforming traditional methods in detecting mild glaucoma. The authors suggest expanding to multi-center studies and incorporating additional data like OCT images for further improvement. The authors in [2] had discussed the "Artificial Intelligence for Glaucoma" session which is AI-based glaucoma detection using fundus photographs, OCT, and SAP. Key findings included a 3D DL system achieving AUCs of 0.893-0.897 and AI predicting structural changes in glaucoma patients. Despite success, the focus is on expediting global access and ensuring external validation for wider clinical use. Veena HN et al.[3] proposed a CNN-based glaucoma detection model that segments the optic disc (OD) and optic cup (OC) from retinal fundus images. Achieving high accuracy (OD 98.76%, OC 97.13%), it outperforms existing models. Image preprocessing, texture-based segmentation, and enhanced CNNs are key components. Challenges include properly segmenting small optic cups surrounded by blood vessels. The authors of [4] proposed a review which highlights AI-enabled glaucoma detection via fundus imaging. It examines AI frameworks, which achieved up to 100% accuracy, but notes limitations in generalizability. While AI mimics expert detection with success, challenges remain in enhancing accuracy and external validation to ensure AI’s widespread clinical application, especially in low-resource settings due to its accessibility. Fan R, Alipour K et al.[5] proposed the study which compares DeiT and ResNet-50 models for glaucoma detection via fundus photographs, showing DeiT’s superior generalizability. With AUROC up to 0.91 on external datasets, DeiT demonstrated better explainability and performance across ethnicities. Limitations include data imbalance and fundus image cropping. DeiT holds promise for scalable deep learning applications in clinical settings. Wang et al.[6] proposed a DL model that was developed to predict glaucoma progression using structured and free-text data from electronic health records (EHRs). The model outperformed others with an AUC of 73%. Including natural language processing improved results. Future work aims to refine models with advanced NLP methods and multi-center validation to enhance clinical decision support. Rizky et al.[7] proposed this research which evaluated deep learning model robustness (ResNet, Vision Transformer, gMLP) against adversarial attacks. Combining DkNN and adversarial training improved model defense for glaucoma severity detection. The optimal k value depended on the attack type. Future work should explore larger datasets and investigate DkNN's performance in adversarial settings for medical applications. Schuman et al.[8] proposed AI models, including deep learning, showed promise in diagnosing glaucoma, especially in moderate stages. This study highlights AI's potential to improve access to care in remote areas by using OCT, VF tests, and fundus photography. However, challenges like bias, data diversity, and health equity must be addressed to ensure effective clinical implementation of AI. García-Jiménez et al.[9] proposed this study used corneal densitometry and machine learning to detect glaucoma risk, achieving 83.93% accuracy. Parameters a(t) and b(t) effectively distinguished suspect glaucomatous eyes. Challenges include overfitting due to a small dataset. While promising, larger datasets and regularization techniques are necessary for robust early glaucoma detection. Chen et al.[10] proposed that AI, particularly deep learning systems, shows high accuracy in glaucoma detection using fundus photos and OCT images, with AUCs above 0.90. However, challenges like subjective ground truth labels and image quality variability hinder clinical application. External validation, device standardization, and addressing high myopia are crucial for improving AI-based glaucoma diagnosis. Gu et al.[11] proposed this review that emphasizes explainable AI’s role in improving clinician trust and adoption. Techniques like LIME and SHapley value help explain AI decisions, enhancing transparency. Diverse data sources and user-friendly interfaces are essential for integrating AI into clinical workflows. While AI shows promise, further development in usability and model transparency is needed for real-world implementation. Juneja et al.[12] proposed CoG-NET, a modified Xception network, classifies retinal fundus images as normal or glaucoma by focusing on optic disc and cup features. Achieving 95.3% accuracy, CoG-NET eliminates manual feature extraction. Its lightweight architecture enables real-world deployment, but further clinical validation on larger datasets is necessary to fully assess its utility in diverse scenarios. Tékouabou et al.[13] proposes C2P EMS2, an ensemble bagging classifier that enhances glaucoma detection using visual field (VF) data. By integrating feature selection and resampling techniques, it improves early glaucoma detection accuracy. Challenges include imbalanced data and model complexity. Further validation with larger datasets is required to refine this approach for clinical use. Kumar et al.[14] proposed this study that combines UNet++ for optic disc/cup segmentation with a ResNet-GRU architecture for glaucoma detection. By combining scores from both regions, detection accuracy improves. The approach, although successful, faces challenges like computational overhead and real-world variability in image quality.

Generalizability across diverse patient data remains a concern for clinical adoption. Świerczyński et al.[15] proposed this novel machine learning approach which uses Triggerfish sensor data and cardiac metrics to detect normal-tension glaucoma over 24-hour periods. Integrating ocular and cardiac data improved accuracy. However, high costs, data availability, and patient inconvenience limit its widespread use. Future research should focus on improving model interpretability and assessing glaucoma progression in longitudinal studies. Christopher et al.[16] proposed multimodal ML models to predict retinal thickness, improving neuroprotection trial efficiency in glaucoma. The approach significantly reduces sample sizes, cutting costs and trial durations. However, cross-sectional data and assumptions about thinning rates limit accuracy. Future work will focus on longitudinal data and advanced methods to further enhance neuroprotection therapy development for glaucoma.

Methodology

1. Data Acquisition and Preparation

- Dataset Collection: A diverse dataset of retinal images, including both healthy and glaucomatous eyes is collected. It is ensured that the images are of high quality and representative of the target population.
- Data Annotation: The images are labelled with relevant information, such as the location of the optic cup and disc, and the overall health status (healthy or glaucomatous).Tools like Roboflow is used for efficient annotation.
- Data Preprocessing: Necessary preprocessing techniques are used to improve image quality and consistency.

2. Data Augmentation

- Create Variations: Additional training data is generated by applying various transformations to the original images.
- Expand Dataset: The dataset size is increased to prevent overfitting and to improve model generalization.

3. Model Selection and Training

- Choose Architectures: Deep learning architectures like ResNet-150 and Inception-V3 are used for classification and U-Net is used for segmentation tasks.
- Train Models: The selected models on the prepared dataset using suitable optimization algorithms and loss functions.

4. Model Evaluation

- Validation Set: The trained models are evaluated on a separate validation set to assess their performance on unseen data.
- Metrics: Relevant metrics to measure the models' accuracy, precision, recall, and loss are used.

5. Hyperparameter Tuning

- Optimize Performance: Experiment with different hyperparameters (e.g., learning rate, batch size, regularization techniques)is done to fine-tune the models and improve their performance.

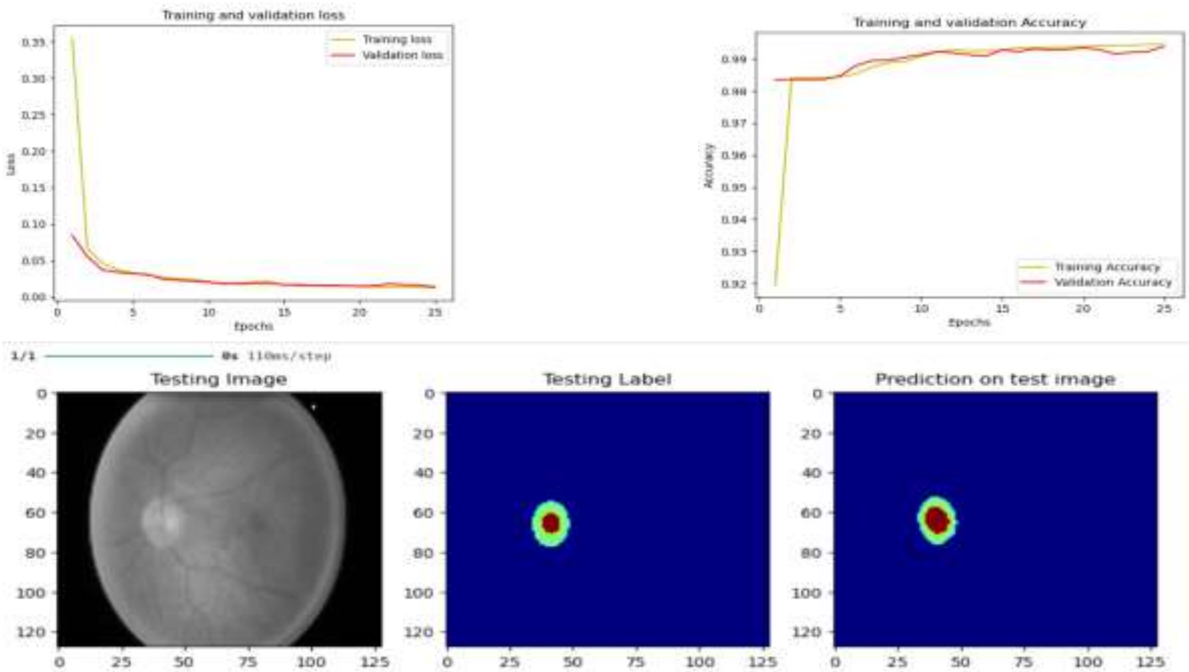
6. Continuous Improvement

- Data Updates: Regularly update the dataset with new images to keep the model's performance current.

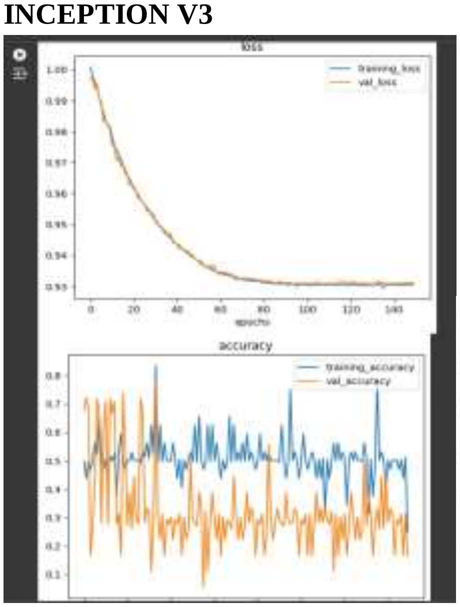
- Model Retraining: Retrain the models periodically to incorporate new knowledge and address evolving challenges.

Result Analysis

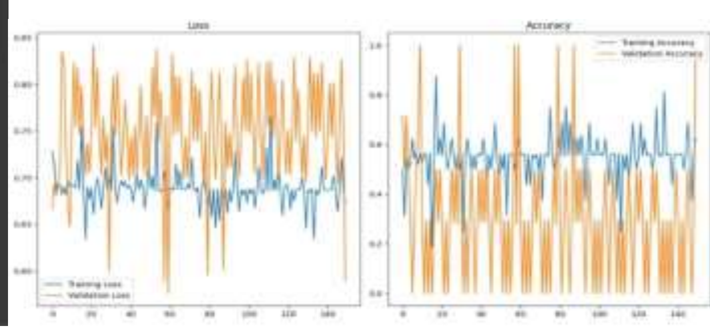
U-NET



INCEPTION V3



RESNET150



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