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Dynamic Fundus Image Processing for Early Detection of Glaucoma

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Abstract - Glaucoma often leads to permanent vision loss without warning signs, so catching it early really matters. Instead of relying on expensive exams or hard-to-reach experts, this tool uses smart automation. It works with regular photos of the back of the eye taken ahead of time. At its heart is a learning- based model called a CNN that checks those images, even if they come from cheap, mobile cameras. People can upload scans safely through a connected system, then talk to eye doctors online. Results get shared fast by local workers who aren't specialists but still help speed up diagnosis. Because it runs on common gear and gives clear feedback quickly, it helps close service gaps where care is limited - giving patients a better shot at saving their sight before it's too late.

Keywords - Glaucoma detection, Fundus image processing, Cup-to-disc ratio, Feature extraction, medical image analysis.

I. INTRODUCTION

Glaucoma damages the eye's main nerve over time, plus it ranks among the top reasons people go permanently blind worldwide. Because it shows no signs at first, catching it fast is crucial so you don't lose sight for good. Checking your eyes early helps reduce harm from this condition - keeping track also matters just as much.

Measuring eye pressure along with checking vision range counts as standard diagnosis. Because they demand special tools besides trained staff, those tests don't work well for mass checks. Snapping pictures of the retina offers a cheaper way that skips invasive steps while showing the optic nerve clearly - making it easier to spot physical shifts.

This study introduces a tool that automatically processes eye images to catch glaucoma sooner. First, it cleans up the pictures - cutting out fuzziness while boosting clarity. Then, it outlines key areas - the optic disc and cup - to focus analysis. After that, it pulls out useful details doctors care about; among them, the CDR stands out, alongside shape traits and surface patterns. With these clues, the system labels each image as healthy or risky, helping flag problems earlier without guesswork.

This automatic method helps eye doctors by cutting down hands-on tasks while boosting reliable results. Built to manage huge batches of images, it works well for wide- reaching check-up efforts. Since it relies less on costly gear, this solution opens doors in areas short on resources. Spotting issues early using image scans can seriously delay worsening conditions - especially when care starts fast. The use of machine learning boosts precision while cutting down mistakes made by people. Still, this method leads to a solid, budget-friendly way to catch glaucoma earlier.

II. RELATED WORKS

Glaucoma creeps in quietly - no signs until it's too late, so spotting it early matters. Khalil's team back in 2014 looked at how machines could help catch it, breaking down steps like cleaning images, pulling out key details, then making predictions. Nikam and Patil came up with a MATLAB tool by 2017 that found the optic disc and cup, figured out edges and thresholds, plus used CDR as a clue for earlier warnings.

Instead of just shapes, Patel and Patel alongside Shetty and Gutte brought textures and fractal patterns into play during 2018, boosting precision through smarter image splitting. Then Carrillo and Bautista refined those splits even more in 2019, introducing fresh ways to measure CDR, helping doctors trust the results.

The latest studies have focused on deep learning, along with methods that use transfer learning to detect glaucoma automatically. Instead of traditional techniques, Saxena and team in 2020 used CNN setups to pull out features step by step.

Moving forward, Arias-Serrano and Velásquez-López two years ago tweaked AlexNet and added Grad-CAM visuals to sort cases of glaucoma plus diabetes-related eye issues. Just lately, Suma’s group in 2025 pointed out how models such as VGG and ResNet are leading the field.

They stressed that cleaning data plus pulling out key details helps boost precision. While deep learning gives solid results, older techniques using CDR along with dividing images still work well since they use less power and are easier to understand. That’s why this project was built - by combining data prep, picking features, then analyzing CDR - to create a flexible system for spotting glaucoma early from eye scans.

III. CNN ARCHITECTURE APPLIED TO GLAUCOMA DETECTION

CNN Architecture

The diagram shows how a CNN usually looks when it's set up to sort images. First comes the input picture - this goes into layers that use filters moving across the image to catch key bits like lines, surfaces, or shapes. Instead of showing everything, these outputs focus on what matters visually by leaving out noise. Afterward, a downsampling step shrinks those outputs, cutting size and processing load but keeping useful traits intact. Once multiple convolutions plus pooling happen, the gathered details get squashed into a single-line string of numbers. That line goes into dense layers that figure out complex links among those numbers. In the end, the last layer gives odds for each category using what it’s seen. Altogether, this step-by-step setup helps CNNs pick up image patterns bit by bit without help

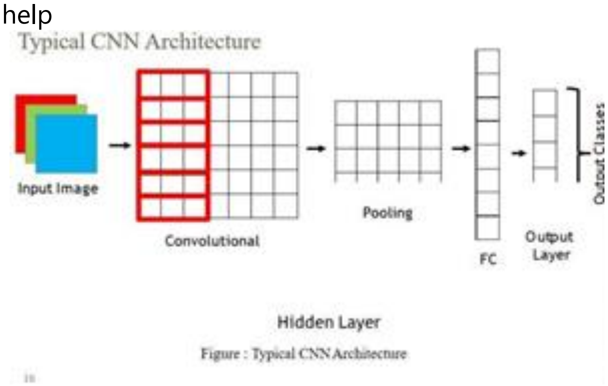

Fig. 1. Typical CNN Architecture

Methedology

In this study, a method to spot glaucoma automatically using retina pictures is introduced. To help clearly see the eye’s disc edge and cup region, images are cleaned up first. After that, key details such as the cup-to-disc size comparison are pulled out - so the system can sort the scans properly.

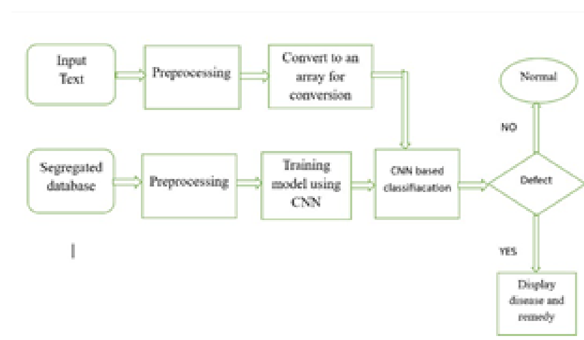

Fig. 2. Proposed Method

Input Image

The input picture shows the inside part of the eye, taken from open medical collections or hospital records. It reveals key areas like the optic disc along with the optic cup - both crucial when checking for glaucoma. How clear and sharp the image is affects how well it can be studied later on. Poor detail might lead to less reliable results during examination.

Preprocessing

Preprocessing boosts image quality by removing noise from the original fundus photo - this could mean adjusting size, turning it grayscale, smoothing out graininess, or sharpening details. It makes blood vessels and retina parts easier to see, setting up clearer inputs before features are learned or labels assigned.

CNN-Based Classification
In this step, cleaned-up images go into a CNN that learns key patterns by itself. This network picks up on visual details tied to damage in the optic nerve area. Because of this, there's no need for hand-picked traits, making it easier to sort cases accurately.

Train model using a CNN
The CNN gets trained using a set of tagged eye images showing healthy and glaucoma-affected eyes. As it trains, the system adjusts its internal settings to reduce mistakes in sorting them right. That way, it picks up how to link visual patterns directly to the correct diagnosis.

Evaluate a Trained Model
The CNN's performance gets checked using fresh test pictures it hasn't viewed before. To confirm dependability, we look at results through measures such as precision along with actual prediction outputs. Doing this helps make sure the system works reliably across unseen examples.

Decision: Defect Detection
The outcome of this check points to whether something's off. When nothing looks wrong, the eye picture gets labeled normal. Should a problem show up, though, it moves on - slotted as glaucoma-like.

Eye pressure issue / Normal result
The system sorts the eye scan as either showing signs of glaucoma or being normal. Doctors can use this result to spot issues early and guide treatment choices. Elevated intraocular pressure is considered a major risk factor in the development and progression of glaucoma, as it can gradually damage the optic nerve.

Results

Sample data sets

The info used here was pulled from Kaggle - holds 720 images of eye scans, some normal, others with signs of glaucoma. While roughly eight in ten were picked for training the CNN, one out of five got reserved for later evaluation. That means 576 pictures fed the learning process, while 144 stayed separate for testing purposes. This division sharpens the model's learning, also offers a truer sense of its real-world performance

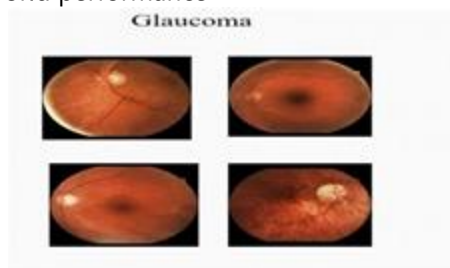

Fig. 3a. Sample Datasets of Glaucoma

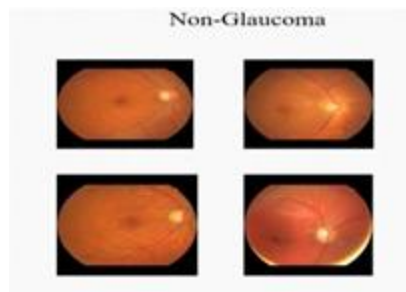

Fig. 3b. Sample Datasets of Non- Glaucoma

Outcome
Early warning signs of glaucoma are key - quick detection boosts treatment success while easing pressure on healthcare centers or doctor offices. When issues show up early, physicians jump in faster, which lowers future costs but also guards eyesight longer term. This is what we tried: first, the optic disc and cup were found by a method known as Hough Circle Transform - it works well for circular patterns in eye scans. Those areas stood out clearly in pictures, allowing measurements near 184 pixels across for the disc, whereas the cup reached about 218 pixels wide. Using these values, the ratio hit 1.18; because this exceeds normal limits, it hints hard at major damage to the nerve involved in seeing

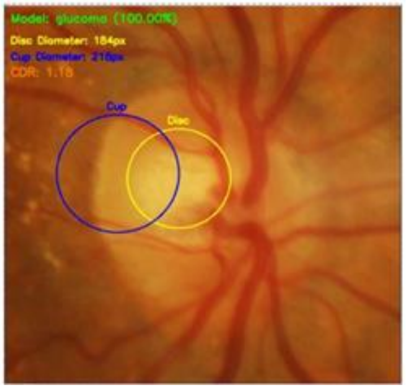

Fig. 3.B Detection of Glaucoma

Fig. 3.B Detection of Non-Glaucoma

Accuracy and Loss Plots

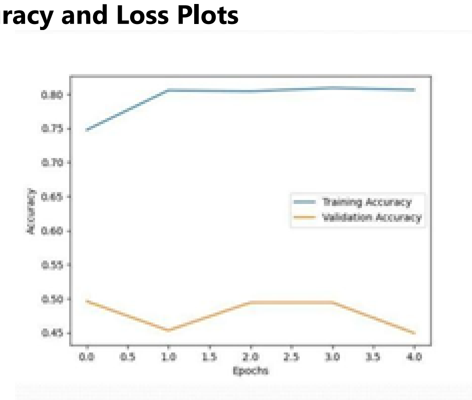

Fig. 3. C. Accuracy Plot

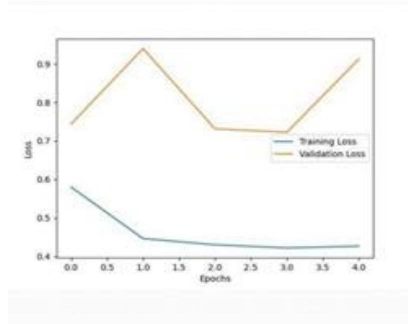

Fig. 3. C. Loss Plot

The training score inches up from 0.75 to about 0.81, meaning the model gradually learns real trends. Still, validation stays shaky - jumping between 0.45 and 0.50 - which hints it struggles with fresh samples, maybe 'cause there's not enough data or image styles differ. Since one number pulls ahead of the other, overfitting might be happening; basically, the system gets familiar with old examples but falters on unknown ones.

The training loss keeps falling steadily - starts at 0.57, ends near 0.43 - which suggests the model learns well over time. Yet validation loss acts shaky; it spikes to nearly 0.95 before dropping again to around 0.72, hinting it's not handling unseen data smoothly. Since one curve moves clean while the other flickers unpredictably, adjusting how harsh we penalize complex patterns could make a difference - or simply adding more samples might do the trick

Comparison with FCNN Model

Performance Comparision of CNN Model with FCNN Model

Fig. 3.D. Performance Comparision of CNN with FCNN Graph

On the flip side, Convolutional Neural Networks don't operate like Fully Connected ones - they're made for picking up visual clues in pictures or medical images, maybe spotting signs of glaucoma. Rather than treating an image like a single row of data, CNNs apply unique layers that examine tiny regions one after another, gradually grabbing features such as edges or forms. Since they remember how pixels are arranged together, these models can locate critical parts of the eye - like the optic disc or cup - in retina scans, boosting early diagnosis chances.

Now FCNNs do things differently - they collapse the entire picture into a sequence, tossing spatial layout out completely. This flattening often removes fine details, meaning FCNNs have a hard time spotting tiny patterns or local shifts - CNNs do better here since they reuse weights and keep links minimal. Thanks to such features, CNNs use way less parameters compared to FCNNs, which means faster training and lower chances of memorizing noise, making them more reliable on unseen examples. Unlike that, FCNNs link each neuron to all in the next layer, requiring loads of extra numbers, spiking both memory load and compute time - particularly when dealing with high-res pictures. Besides, CNNs adjust easily to moved, rotated, or resized objects without special tweaks, whereas FCNNs mostly depend on heavy preprocessing or expanded data sets to reach similar robustness.

CNNs often learn faster because they focus on spatial patterns rather than tangled connections - something FCNNs waste time on. While FCNNs handle simple or flatter data just fine, CNNs clearly win when images grow complex. In medical imaging, where small details are critical, CNNs find correct signs more reliably while skipping false alarms. Beyond that, CNNs mix easily with techniques like tweaking pre-trained models to lift performance higher - a move FCNNs can't manage well. Overall, the way CNNs are built suits visual tasks best - they grab features sharper, use less power, adjust easier, resist noise better than FCNNs, so they're the solid choice for deep image analysis.

Discussions & Future Work

The future of tracking eye movements to find glaucoma is full of potential, opening paths to make these tools quicker, more precise, and practical in real medical settings. Rather than old-style models, advanced network layouts - such as those using focus-based CNNs or blends of CNNs with transformer systems - can highlight critical retinal areas while capturing clearer signals, making early detection easier. Combining this info with other imaging methods - like OCT or dye-based angiography - brings in added details on structure and circulation, boosting diagnostic clarity. Creating larger, diverse sets of accurately tagged images would let software perform consistently across populations, reducing bias and improving performance beyond controlled environments. On top of that, straightforward AI lets doctors follow how conclusions are reached - so trust grows, and clinics actually start using it. Rather than delays, real-time setups could hook up with portable eye scanners, delivering exams to neighborhoods or remote spots via online links.

Not limited to glaucoma - it may catch diabetic harm, age-related decline, or nerve troubles, making it a broad-spectrum eye helper. Later on, research might blend prediction models to monitor progression and recommend personalized treatments. Altogether, the goal is building sharp, adaptable, open systems for analyzing eye images - spotting glaucoma earlier while boosting prevention and cutting preventable vision loss across the globe

IV. CONCLUSION

In brief, studying video scans of the eye's inner back layer reveals how machines detect first signs of glaucoma. With advanced image processing combined with strong learning models, they accurately mark crucial spots such as the optic disc and cup. Then it calculates their relative sizes - known as CDR - and notices small changes linked to worsening conditions. Since this approach tweaks itself according to brightness, sharpness, or individual eye forms, outcomes remain stable. This tech skips slow, error-heavy doctor inspections, delivering clear data for faster decisions. Because trials reveal strong precision spotting actual issues without triggering unnecessary warnings, it's shown to genuinely support diagnosis work. By combining live image scanning with clever code, the effort highlights a way to detect glaucoma sooner - critical for preventing lasting vision loss. Even though automatic aids won't swap routine eye tests, they bring benefits like quicker screenings, lower expenses, also improved reliability - especially helpful when clinics face high demand or tight budgets.

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