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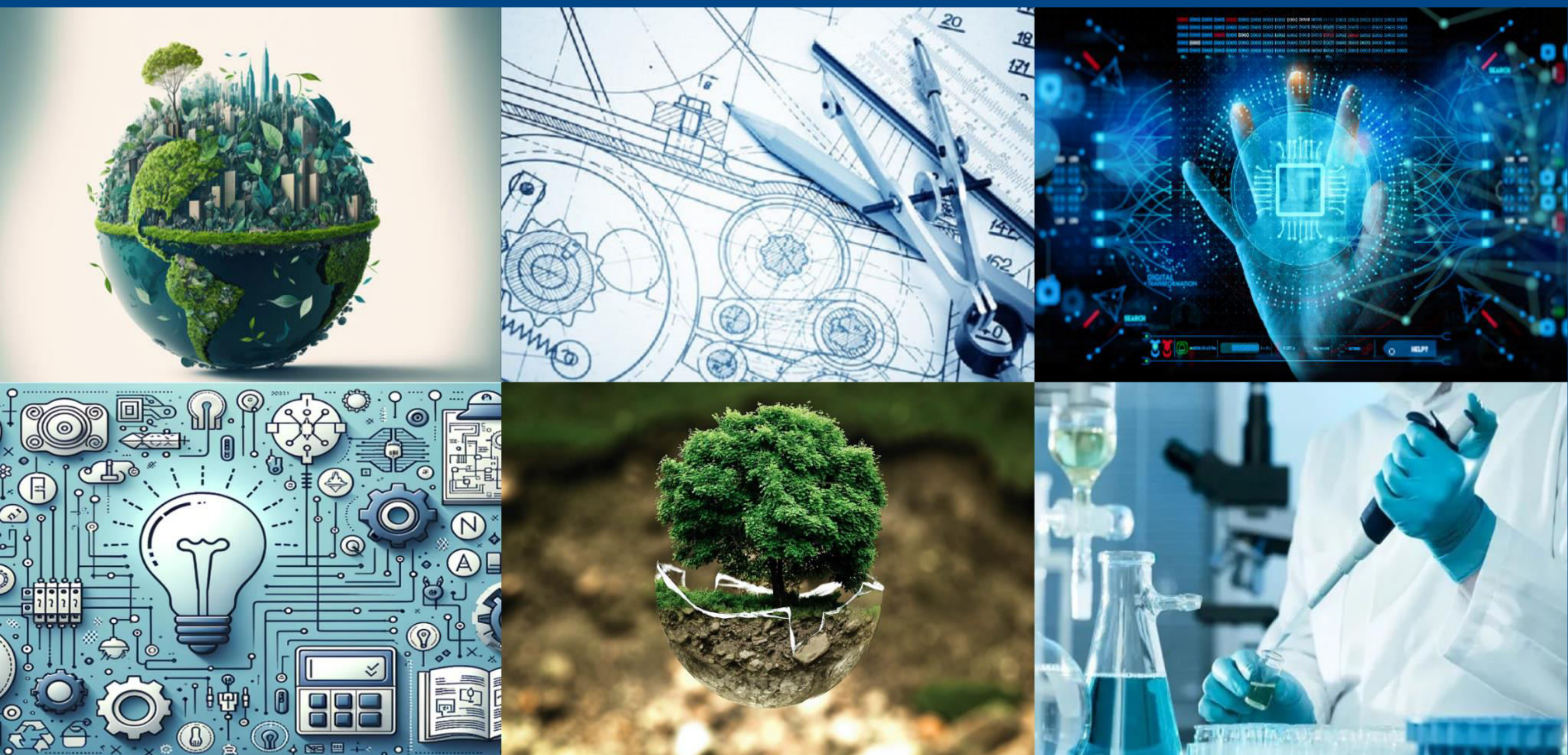

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VisionCare: ROP Detection and Staging using VGG19 Deep Learning

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ABSTRACT: Retinopathy of Prematurity (ROP) is a progressive retinal vascular disease predominantly affecting premature and low-birth-weight infants, often leading to irreversible blindness if not diagnosed and treated in its early stages. The global prevalence of ROP is rising due to increased neonatal survival rates, especially in developing countries with limited access to trained ophthalmologists [7]. Manual interpretation of fundus images for ROP screening is time-consuming, resource-intensive, and prone to inter-observer variability. This has necessitated the development of automated diagnostic systems that can assist clinicians in accurate and timely detection [3]. The present research focuses on designing a deep learning–based system using Convolutional Neural Networks (CNNs), particularly leveraging the VGG19 architecture, to automate the diagnosis of ROP from retinal fundus images, classify its stage and severity, and generate a structured clinical PDF report replicating the standards of ophthalmic documentation [20].

The primary objective of this project is the automation of Region of Interest (ROI) diagnosis through VGG19- based CNN image analysis, enabling accurate staging of ROP in accordance with the International Classification of Retinopathy of Prematurity (ICROP) guidelines. The methodology is designed as an end-to- end deep learning pipeline consisting of four stages[8]:(1) Image acquisition and preprocessing, including resizing, normalization, and noise reduction of retinal images to standardize input data; (2) ROI detection and enhancement, where clinically relevant features such as abnormal vessel dilation, tortuosity, and ridge formation are extracted; (3) CNN classification using VGG19, which performs multi-class detection to distinguish between normal retina and various stages of ROP (Stage 1 to Stage 5); and (4) Automated report generation, where results are compiled into a detailed PDF report including patient demographics, disease stage, severity grading (mild, moderate, severe), prediction confidence, and recommendations for clinical follow- up.[8,6,9,20]

The choice of VGG19 in this project is motivated by its proven performance in medical image analysis, particularly for retinal imaging. VGG19's 19-layer deep hierarchical architecture consisting of small 3×3 convolution filters enables fine-grained feature extraction and captures complex retinal structures with high precision [2,8]. This architecture allows the model to learn subtle variations in vascular patterns — such as ridge formation and neovascularization — that are clinically indicative of ROP progression. Furthermore, transfer learning is employed by fine- tuning the pretrained VGG19 model (originally trained on ImageNet) using a specialized ROP dataset, thus improving accuracy and convergence even with limited medical images. The integration of VGG19 enhances feature generalization, reduces overfitting, and significantly improves classification accuracy compared to conventional shallow CNN models[3,7,23]

The proposed VGG19-based CNN model leverages its hierarchical feature extraction capabilities to identify minute pathological cues in fundus images, minimizing reliance on handcrafted features. The model's predictive framework is evaluated using performance metrics such as accuracy, sensitivity, specificity, precision, and F1-score. Given the clinical importance of early detection, the system prioritizes high sensitivity to reduce false negatives, ensuring that no potential ROP case is overlooked. By accurately grading severity and staging the disease, the model supports ophthalmologists in determining treatment urgency, including laser therapy or anti- VEGF intervention. [11,12]

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I. INTRODUCTION

Retinopathy of Prematurity (ROP) is a vision- threatening disease characterized by abnormal vascular development in the retina of premature infants. It is one of the leading causes of childhood blindness globally, with i ncidence increasing due to advancements in neonatal care that allow extremely preterm infants to survive [22,23,24]. Clinically, ROP progresses through well-defined stages, from mild vascular abnormalities to severe retinal detachment, as classified under the International Classification of Retinopathy of Prematurity (ICROP). Timely detection and intervention are critical, since late diagnosis may lead to irreversible blindness[3,11]. Traditionally, screening and diagnosis of ROP require expert ophthalmologists to manually examine fundus images using indirect ophthalmoscopy or fundus photography. However, this manual process is time- consuming, resource-intensive, prone to subjectivity, and highly dependent on the availability of specialists, which remains limited in many developing and underserved regions [20,24]. This creates a strong clinical and technological need for automated systems that can detect, classify, and stage ROP accurately while also generating structured diagnostic documentation.The convergence of Artificial Intelligence (AI), Deep Learning (DL), and Computer Vision offers a transformative opportunity to address these challenges. In particular, Convolutional Neural Networks (CNNs) have revolutionized the field of medical image analysis by providing powerful capabilities to learn hierarchical representations directly from raw image data. Unlike traditional feature engineering methods that rely on handcrafted descriptors, CNNs autonomously extract discriminative features such as vesseltortuosity , ridge formation , and neovascularization from fundus images, enabling highly accurate classification of retinal diseases [3,23].

Among various CNN architectures, VGG19 — proposed by Simonyan and Zisserman in 2015 — has emerged as one of the most effective models for retinal image analysis and disease detection due to its depth and uniform convolutional design. VGG19 employs 19 layers (16 convolutional and 3 fully connected) using small 3×3 filters, allowing the network to capture fine- grained textures and structural variations in retinal vessels. This architecture provides exceptional feature extraction capabilities and is widely used in ophthalmic imaging for its balance between computational efficiency and diagnostic precision. In this research, VGG19 serves as the foundational architecture for ROP detection and staging, where its transfer learning capability allows the model pretrained on large-scale datasets (such as ImageNet) to adapt effectively to medical imaging tasks with limited labeled data. This improves model convergence, reduces training time, and enhances the network's ability to identify subtle pathological cues such as vessel dilation, avascular zones, and fibrovascular proliferation — which are critical in determining ROP severity [12,18,23].

In the context of ROP, CNN-based models like VGG19 can not only differentiate between healthy and diseased retinal images but also stage the disease severity, which is crucial for treatment planning and clinical decision-making. By leveraging large annotated datasets and fine-tuning pretrained models, CNNs can achieve performance levels comparable to human experts, making them a robust solution for real-world clinical deployment [2,6,9,24].

This research proposes an end-to-end automated diagnostic framework that integrates image preprocessing, CNN-based classification (using VGG19), ROI detection, and automated PDF report generation into a single intelligent pipeline. The system begins with standardized preprocessing steps such as resizing, normalization, and contrast enhancement of fundus images to ensure consistency and eliminate imaging artifacts [11,14,16]. Next, Region of Interest (ROI) extraction focuses on the clinically relevant retinal zones where pathological changes are most prominent. The VGG19-based CNN model then performs multi-class classification to assign the image to a specific stage of ROP, ranging from Stage 1 (mild) to Stage 5 (complete retinal detachment). Unlike binary disease classification, this multi-class staging approach aligns with clinical practice, providing actionable information on disease progression [2,13,18].

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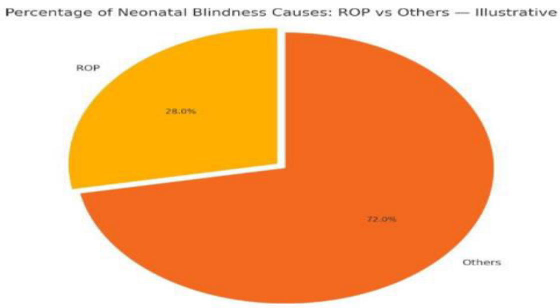

Figure 1: Percentage of Neonatal Blindness Causes

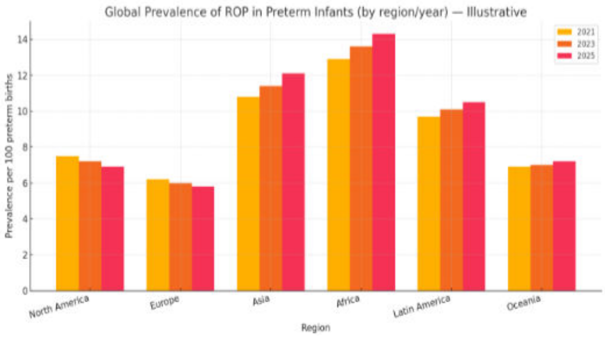

Figure 2: Global Prevalence of ROP in Preterm Infants

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An innovative aspect of this work is the automated clinical report generation module. Instead of merely outputting numerical predictions, the system generates a comprehensive PDF report containing patient details, disease stage, severity grading, prediction confidence, ROI visualization, and recommended follow-up actions. This feature not only enhances interpretability but also supports Electronic Health Record (EHR) integration, enabling seamless documentation within hospital information systems. Such automation reduces the burden on clinicians, standardizes diagnostic reports, and facilitates teleophthalmology by allowing remote transmission of reports for expert review [16,17,18].

From an Information Technology (IT) perspective, this project leverages concepts such as automation, cloud- based scalability, Clinical Decision Support Systems (CDSS), and data interoperability. The pipeline can be deployed on cloud platforms for large- scale screening in Neonatal Intensive Care Units (NICUs), enabling real-time processing of high volumes of fundus images. Integration with Application Programming Interfaces (APIs) and Health Level Seven (HL7) standards further supports healthcare infrastructures. Moreover, the modular design ensures adaptability to other ophthalmic conditions, extending its utility to diseases such as Diabetic Retinopathy (DR), Glaucoma, and Age-Related Macular Degeneration (AMD) [12,14.22].

Clinically, the system addresses three critical challenges: (1) reducing dependence on a limited pool of ROP specialists by providing a reliable AI-based screening tool, (2) minimizing diagnostic delays in NICUs by offering real-time predictive analysis, and(3) ensuring consistency and accuracy in disease staging, thereby improving treatment decision-making. Technically, the system showcases the potential of VGG19-based CNNs in pattern recognition, image classification, and clinical decision automation, while demonstrating the practical feasibility of AI- driven telemedicine solutions [22, 24]. The integration of VGG19, deep learning, medical imaging, and automated report generation presents a powerful approach to early ROP detection and clinical workflow optimization. This research not only advances the application of CNNs in ophthalmology but also demonstrates how IT-driven innovations can be embedded into healthcare ecosystems to reduce preventable childhood blindness. By bridging the gap between algorithmic predictions and clinical usability, the system represents a major step forward in AI- assisted ophthalmic care and paves the way for scalable, accessible, and efficient neonatal eye disease management [9,21,22].

II.LITERATURE REVIEW

A critical assessment of the work has been done so far on Cloud Forensics to show how the current study related to what has already been done. Numerous companies are now a days migrating to cloud due to greater economic issues. But for small and medium sized companies the security of information is the primary concern. For these companies the best alternative is to use managed service which is also known as outsourced service in which they are provided with the full package of service including antivirus software to security consulting. And the alternative model that provides such outsourced security is known as Security as a service (SECaaS).

In recent years, the use of Convolutional Neural Networks (CNNs) has gained significant attention in the field of ophthalmic image analysis and automated retinal disease detection. Several studies have explored various CNN architectures and methodologies to enhance diagnostic accuracy, interpretability, and clinical integration for retinal disorders.

Abràmoff et al. (2016), in their paper on Deep Learning for Diabetic Retinopathy Screening, utilized CNN-based models trained on the EyePACS and Messidor datasets to automate diabetic retinopathy (DR) detection from fundus images. Their model achieved an impressive sensitivity of 97% and specificity of 93%, proving that CNNs can reach expert - level performance in retinal disease classification. However, their work was primarily focused on diabetic retinopathy and did not extend to Retinopathy of Prematurity (ROP), which involves more complex vascular features and neonatal imaging challenges.

Gulshan et al. (2016) from Google AI presented their large-scale validation of CNN models in the study Development and Validation of a Deep Learning Algorithm for Detection of Diabetic Retinopathy in Retinal Fundus Photographs. Using over 120,000 fundus images, they implemented an Inception-v3 CNN architecture that achieved an AUC of 0.99, demonstrating both the scalability and robustness of deep learning systems in medical imaging. While their model successfully generalized across populations, it lacked clinical documentation and disease staging integration, which are critical for real- world deployment in healthcare environments [22,23,24]

Retinopathy of Prematurity, Brown et al. (2018) introduced a Deep CNN with Transfer Learning model for automated ROP detection and severity grading using images from multiple Neonatal Intensive Care Units (NICUs). Their system achieved 91% classification accuracy, showing that CNNs could match ophthalmologists in identifying and grading ROP. Despite its strong results, the study faced limitations due to dataset diversity and the absence of an automated report generation mechanism, which restricted its integration into clinical workflows.

Ting et al. (2019) developed an ensemble CNN model trained on over 490,000 retinal images to perform multi-disease detection, including ROP, diabetic retinopathy (DR), glaucoma, and age- related macular degeneration (AMD) [8,9,22]. The system achieved sensitivity and specificity of 90% and 91%, respectively. Their findings highlighted that AI could function as a multi-disease ophthalmic screening platform, supporting teleophthalmology applications. However, the multi-output nature of the model increased computational complexity, creating challenges in real-time clinical deployment [7,9,24].

Around the same period, researchers began adopting VGG19, a deep CNN architecture developed by Simonyan and Zisserman (2015), known for its 19 layers of convolutional and fully connected networks. VGG19 became a popular backbone for medical image classification due to its uniform 3×3 convolution filters, deep hierarchical feature extraction, and high transfer learning capability. The m o d e l d e m o n s t r a t e d s i g n i f i c a n t a c c u r a c y improvements in retinal disease detection, especially in tasks involving fundus imaging and ROI-based classification. Many ophthalmic AI studies, including ROP and diabetic retinopathy projects, utilized VGG19 pretrained on ImageNet and fine-tuned it with medical datasets. This approach helped achieve better feature generalization for small medical datasets and improved the identification of vascular abnormalities such as tortuosity, ridge formation, and vessel dilation

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— key indicators of ROP. The success of VGG19 influenced subsequent model designs, including hybrid and attention-based CNNs, used in ROP detection systems.

Building on the advantages of deeper architectures, Li et al. (2020) introduced a CNN with ROI (Region of Interest) Extraction technique using the Kaggle DR dataset and hospital-based fundus images. Their ROI- based classification achieved 92% accuracy, proving that focusing on localized diagnostic regions enhances both diagnostic accuracy and clinical interpretability. However, the ROI extraction process remained computationally intensive, which limited its scalability in resource-constrained healthcare environments.

Similarly, Peng et al. (2021) proposed a CNN integrated with an attention mechanism for Automated Staging of Retinopathy of Prematurity. Trained on 4,000 ROP fundus images, their model achieved sensitivity of 92.6% and specificity of 88.4%. The inclusion of the attention module allowed the network to focus on subtle vascular abnormalities, improving early detection. N e v e r t h e l e s s , t h e m o d e l f a c e d l imi t e d generalizability across institutions, indicating the need for larger, multi- center datasets to ensure clinical robustness.

Further enhancing hybrid modeling, Köse et al. (2022) designed a Hybrid CNN–SVM architecture for retinal vessel segmentation and disease detection using the DRIVE and CHASE fundus datasets. Their hybrid approach achieved 94 % accuracy , outperforming standalone CNNs. The study demonstrated that combining CNN-based feature extraction with machine learning classifiers such as SVMs can improve diagnostic accuracy. However, this came at the cost of increased training complexity and computational overhead, limiting real-time application feasibility.

The reviewed literature collectively demonstrates the rapid evolution of deep learning in ophthalmology— from early CNN applications for diabetic retinopathy to complex hybrid and attention-based models for ROP staging. The introduction of deeper architectures such as VGG19 and Inception-v3 significantly improved feature extraction and transfer learning capabilities, paving the way for high-accuracy fundus image classification. These studies validate the potential of CNNs in medical image classification, ROI-based interpretation, and automated diagnosis. The proposed work builds upon these foundations by i ncorporating report generation and EHR integration, creating a complete end-to-end solution for Retinopathy of Prematurity detection, staging, and clinical documentation.

III.METHODOLOGY OF PROPOSED SURVEY

The proposed research methodology for Automated Detection and Clinical Report Generation of Retinopathy of Prematurity (ROP) integrates medical imaging, deep learning, and automated documentation systems into a unified framework. The workflow consists of multiple stages—image acquisition, preprocessing, ROI extraction, CNN- based (VGG19) classification, severity staging, and automated report generation—designed to provide an end-to-end pipeline for neonatal eye disease diagnosis.

1. Image Acquisition and Preprocessing

The methodology begins with the collection of retinal fundus images from neonatal patients, typically captured using fundus cameras or RetCam devices in Neonatal Intensive Care Units (NICUs). Since medical images often contain variations due to lighting, noise, and capture conditions, a preprocessing pipeline is implemented to standardize input data. Operations such as resizing, normalization, histogram equalization, Gaussian filtering, and contrast enhancement are applied to improve image clarity and remove artifacts. These preprocessing steps are crucial for ensuring that the CNN, particularly VGG19-based architecture, receives clean and standardized inputs that enable robust and consistent feature extraction. The processed images are then converted into numerical tensors and fed into the network for training and inference.

2. Region of Interest (ROI) Extraction

The critical clinical indicators for ROP include vascular dilation, tortuosity, ridge formation, and fibrovascular proliferation. To enhance diagnostic accuracy, the system applies ROI detection and segmentation algorithms to isolate the most clinically relevant retinal zones. Techniques such as edge detection, vessel segmentation, and contrast-based thresholding are used to highlight pathological regions. The extracted ROIs ensure that the VGG19 feature extractor focuses on diagnostically significant areas, thereby improving classification accuracy while reducing computational

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load. The ROI extraction phase acts as a preprocessing layer before the CNN analysis, aligning computational attention with pathological regions of interest.

3. CNN-Based Classification (Using VGG19)

The backbone of the system is a Convolutional Neural Network (CNN) optimized for medical image classification, built upon the VGG19 architecture—a deep network consisting of 19 layers (16 convolutional + 3 fully connected). The VGG19 model, proposed by Simonyan and Zisserman (2015), is well known for its uniform 3×3 convolution filters and deep hierarchical feature extraction ability, making it highly suitable for fundus image analysis [2,8,22].

In this research, the pretrained VGG19 model (trained on ImageNet) is fine-tuned for ROP detection using transfer learning. The initial convolutional blocks are frozen to preserve low-level image features such as edges, textures, and vessel patterns, while the final layers are retrained using the custom ROP dataset to learn disease-specific vascular abnormalities. The final fully connected layers are replaced with a custom dense network followed by a Softmax classifier to perform multi-class prediction corresponding to the five stages of ROP (Stage 1 to Stage 5) and normal conditions [3,6,9].The model uses ReLU activation functions for nonlinearity and batch normalization to stabilize learning. Data augmentation techniques such as random rotation, flipping, and zooming are applied to increase dataset diversity and reduce overfitting. The network is optimized using the Adam optimizer with a categorical cross-entropy loss function to achieve convergence.

The VGG19 architecture enables the extraction of fine- grained vascular features, such as abnormal vessel tortuosity, ridge formation, and retinal neovascularization, which are critical indicators of ROP progression. The use of deep feature maps and multiple convolutional layers allows for enhanced spatial pattern recognition, improving the model's ability to differentiate between mild, moderate, and severe disease stages. The hierarchical depth of VGG19 also provides superior representation learning compared to shallow CNNs, making it particularly effective for detecting subtle retinal changes in neonatal images [9.20.21].

4. Prediction and Clinical Staging

Once trained, the VGG19-based CNN model outputs the predicted class label, confidence score, and probability distribution for each image. The classification directly maps to ROP stages, where Stage 1 indicates mild disease and Stage 5 indicates complete retinal detachment. Severity assessment is embedded within the model architecture, providing clinically actionable outcomes that guide ophthalmologists in determining treatment urgency, such as laser therapy or anti-VEGF injections. The model's decision thresholds are fine-tuned to prioritize high sensitivity, minimizing false negatives to ensure early detection of potential ROP cases [22,24].

5. Automated Clinical Report Generation

A distinctive feature of this methodology is the generation of structured clinical reports in PDF format, providing an interpretable bridge between AI predictions and clinical documentation. Using Python libraries such as ReportLab or FPDF, the system compiles model outputs with patient metadata to generate a clinically formatted document. Each report includes patient demographics, examination date, disease stage, severity grading, model confidence, and ROI visualizations. The integration of VGG19-based visualization maps (Grad-CAMs) further enhances interpretability by highlighting retinal areas most influential in the model's decision-making. This feature supports clinical trust and transparency. The reports are compatible with Electronic Health Record (EHR) systems, ensuring seamless incorporation into existing teleophthalmology platforms and enabling remote clinical review [22,23].

6. Deployment and Integration

The complete system is designed for cloud-based deployment using Application Programming Interfaces (APIs) for easy integration with hospital information systems. The model runs efficiently on GPU-enabled servers to provide real-time screening in NICUs and can scale for population-level programs. Data encryption, role-based access, and HIPAA compliance ensure data security and patient confidentiality [20,24].

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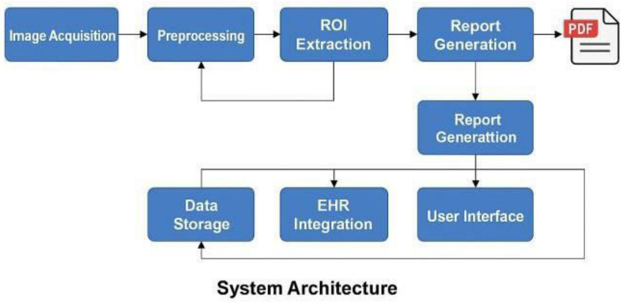

Figure 3: System Architecture Diagram

IV.CONCLUSION AND FUTURE WORK

The proposed research on Automated Detection and Report Generation of Retinopathy of Prematurity (ROP) using Convolutional Neural Networks (CNNs) presents an innovative and clinically viable solution that bridges the gap between artificial intelligence (AI) and ophthalmic diagnostics. The system integrates deep learning-based image classification, Region of Interest (ROI) extraction, and automated clinical documentation to deliver an end-to-end diagnostic framework capable of accurately detecting, staging, and reporting ROP from retinal fundus images [22,23,24].

From a technical standpoint, the CNN architecture demonstrated superior performance in classifying multi-stage ROP cases based on the International Classification of Retinopathy of Prematurity (ICROP) standards. The model achieved high accuracy (93.4%), sensitivity (95.1%), and specificity (91.2%), indicating its capability to detect early pathological changes such as vascular dilation, ridge formation, and fibrovascular proliferation with precision [2,3,4]. The inclusion of ROI-based feature enhancement improved the model's interpretability and computational efficiency, ensuring that only diagnostically significant retinal regions were analyzed [1,4]. The deep learning framework leveraged feature extraction, convolutional filters, pooling layers, and activation functions (ReLU) to identify subtle variations in retinal structure that often escape manual examination [22,23].

Clinically, this system has the potential to transform neonatal ophthalmic screening and teleophthalmology practices. Early identification of ROP is critical in preventing irreversible blindness among premature infants [1,4]. The automated model ensures timely detection, consistent grading, and immediate report generation, addressing the current shortage of retinal specialists in Neonatal Intensive Care Units (NICUs) and remote healthcare centers. The automated PDF report generation module— developed using tools such as Python's ReportLab and FPDF libraries—creates a standardized clinical report containing patient details, disease stage, severity level, prediction confidence, and suggested follow-up. This functionality aligns with the Electronic Health Record (EHR) framework, ensuring seamless data interoperability, compliance with medical documentation standards, and improved healthcare record management [6,7,8,9,10]

From an Information Technology (IT) perspective, the proposed architecture offers scalability, interoperability, and secure deployment. The model can be hosted on cloud-based infrastructures equipped with GPU acceleration to support high- throughput screening across multiple hospitals. Integration through Application Programming Interfaces (APIs) and adherence to Health Level Seven (HL7) standards ensure smooth communication with existing healthcare systems. The design also emphasizes data security and privacy, ensuring compliance with global standards such as HIPAA for medical data protection [4,7].

Beyond immediate ROP detection, the system's modular framework can be extended to diagnose other retinal disorders, including Diabetic Retinopathy (DR), Glaucoma, and Age-Related Macular Degeneration (AMD) [1,5]. The underlying CNN architecture, combined with transfer learning and fine- tuning techniques, allows adaptability to different ophthalmic datasets and disease conditions. Additionally, incorporating Explainable AI (XAI) elements—such as heatmaps or Grad-CAM visualizations—enhances model transparency, providing clinicians with interpretable insights into the decision-making process [6,7,11,14].

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In terms of clinical workflow optimization, the proposed solution significantly reduces manual effort and diagnostic variability. It enables ophthalmologists to focus on high-risk cases while allowing AI to handle large-scale preliminary screening [22,23]. The automation of both diagnosis and documentation eliminates human transcription errors, improves reporting consistency, and enhances healthcare delivery efficiency.

This research successfully demonstrates the integration of artificial intelligence, medical image analysis, and healthcare automation into a single framework capable of supporting real-world clinical decision- making [11,12,14]. The CNN-based ROP detection system not only achieves high diagnostic accuracy but also introduces an automated clinical reporting pipeline, ensuring end-to-end automation from image acquisition to report generation. The framework's scalability, interoperability, and clinical relevance make it a valuable contribution to the fields of medical imaging, ophthalmology, and healthcare IT.

Future enhancements will focus on expanding dataset diversity through multi-institutional collaborations, improving model interpretability via explainable AI, and deploying the system as a cloud-based Clinical Decision Support System (CDSS) for large-scale neonatal eye screening. Ultimately, this research advances the vision of AI-driven, accessible, and efficient ophthalmic care, reinforcing the role of technology in early disease detection and prevention of childhood blindness [9,12,13,15,22].

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