Trustworthy Retinopathy Of Prematurity Diagnosis Using Explainable Vision-Language Model

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Retinopathy of Prematurity (ROP) remains one of the leading causes of preventable childhood blindness, particularly in low-resource settings where specialist access is limited. Although deep learning has improved automated ROP detection, most existing models rely solely on retinal images and function as opaque black boxes, limiting clinical trust and realworld adoption. This study proposes a robust and trustworthy ROP diagnosis framework that combines Vision-Language Modeling (VLM) and Explainable AI. The pipeline fuses high-resolution wide-field retinal fundus images with neonatal NICU text records using a lightweight Vision Transformer, a clinical text encoder, and a neuro-symbolic reasoning layer for human-in-the-loop corrections. A key technical enhancement applies Weighted-Fuzzy Histogram Equalization (WFHE) to boost local vascular contrast while avoiding artifacts, outperforming Contrast Limited Adaptive Histogram Equalization CLAHE in highlighting subtle pathological cues. Evaluations on benchmark ROP datasets, paired with semi-structured NICU reports, demonstrate that the multimodal system improves diagnostic AUC by 7-9 % compared to image-only baselines, and delivers dual explanations through Grad-CAM heatmaps and SHAP token-level attributions. Structured clinician feedback confirms that the system's explanations align with expert annotations and improve interpretability and trust. This framework demonstrates that integrating WFHE, Vision-Language fusion, and multi-level explainability can enable transparent, deployable AI for equitable neonatal vision care.

Keywords: Multimodal fusion; Neonatal retinal screening; Neuro-symbolic reasoning; Weighted-Fuzzy Histogram Equalization (WFHE)

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1. Introduction

Retinopathy of prematurity (ROP) is one of the main causes of vision impairment and blindness among children worldwide, with the highest burden observed in South Asia and SubSaharan Africa, where disparities in neonatal care standards persist [1]. In the past thirty years, the vision loss burden caused by ROP has raised by more than 30 % globally. This includes moderate and severe vision loss. This growing strongly contributes to childhood blindness worldwide [2]. Recent studies explained that large-scale, multicenter deep learning platforms can enhance the screening of ROP. It is also demonstrated, by these studies, high accuracy diagnosis and integration of explainability support scalable implementation [3]. Reviews cross countries confirm wide variations in ROP incidence. These variations are largely driven by disparities in neonatal intensive care standards, oxygen regulation practices, and the availability of consistent screening protocols [4]. Recent predictive modeling studies show that the ROP occurrence and severity reflect the quality of neonatal care. The probability of ROP occurrence and severity are especially occur in preterm infants with low birth weight and early gestational age [5]. These trends are similar to what we see in other rare but severe

childhood disease. These diseases cause many problems for children and families. One example is recessive dystrophic epidermolysis bullosa (RDEB) [6]. Since the healthcare becomes more digital, doctors willingness to share electronic medical records influences the performance and integration of AI-driven healthcare systems. In order to ensure that AI systems will work well, this sharing is very important. For the sake of trustworthy systems design, it is very important to understand how doctors behave in different levels of decision [7]. In fact, many modern healthcare systems run on IoMT platforms and for this reason, they need setups that are safe and flexible. These setups should be able to grow and handle extra works. Blockchain technology, which adds another layer of protection, can also be used in order to strengthen the security [8]. Around 32,000-45,000 cases of Retinopathy of Prematurity (ROP) are reported annually, and most cases occur in the countries that have low income. The number of ROP raises in places where newborn care is improved, but screening systems have not advanced at the same rate and this results in more untreated cases. In fact, less than 40 % of babies who need screening receive it on time in countries such as India, Nigeria, and Bangladesh. This happens because there are not enough retina cameras and the lack of trained eye specialists. Manual grading of fundus images also has weakness. Early changes in blood vessels can be subtle, and they are often missed. In many cases, different doctors may give different results. So, the process of manual grading is slow, not automated, and does not work equally well across various devices or populations. In addition to that, it is difficult to distinguish between early and advanced stages of the disease. All these reasons show the urgent need for smart, clear, and scalable diagnostic tools that support global healthcare systems [4].

Global and regional trends of incidence demonstrate the increasing gap. Present spatiotemporal analysis suggests that the burden of ROP is increasing, with large between country discrepancies particularly in South Asia and Sub-Saharan Africa where extensive neonatal care capabilities are still underdeveloped and universal levels of screening guidelines yet to be established [1]. More recently, cross-country surveys have also measured such differences, with extensive between-region variations in incidence and coverage that are strongly associated with neonatal care capacity and protocol compliance [1, 2]. In the resource-limited societies which are distributed and have poor access to medicine, with low coverage, and follow-up rate, there can be missing early detection and referral of patients in time [4]. These trends are magnified in preterm LBW and extremely early GA infants suggesting the wide-ranging risk profile (when considered by predictive modeling studies [5]). From a daily clinical perspective, programs of screening in developing and emerging Countries have to face many operational criticalities: scarcity of wide-field fundus cameras, lack of pediatric retinal specialist physicians, fractured systems for patient referral and rapport with other services, variability of data quality that hampers Long-term observational exercises. And, even if screening is started, a deficiency of personnel and equipment mean the frequency at which tests can be done are stretched out such that there is increased risk of progression to second stage before the detection with routine workflows. This throughput bottleneck is a risk for both loss-to-follow-up and progression to treatment requiring disease in infants before reassessment [4]. Jointly, these limitations emphasize the demand for scaling tools with limited resources but high sensitivity to early disease.

The latest studies, including the systematic review suggest that deep learning (DL) algorithms for ROP diagnosis on retinal fundus images reach near-human or superior accuracy [9, 10]. However, such models frequently are "black boxes" opaque to interpretation for clinical end-users which may result in fairness, bias and generalizability issues if diversity of training data and transparency is not considered [11]. Meta-analyses, as well as practical cases, stress the absence of a standardized explainability and its impact to wide spreading of use in the neonatal care [12]. Furthermore, cross-regional audits demonstrate that delayed screening and poor follow-up continue to be leading causes of avoidable ROP blindness in LMICs [4].

It can be seen that, technically, point of care diagnostic methods have specific limitations. Manual grading for fundus images is a traditional approach that has problems such as interrater variability, and variable sensitivity to subtle vascular change and their early stage differentiation being difficult and device-dependent. It is at the mild end of disease where these limitations are most severe [10, 11] and subtle vascular alteration result in early lesions being missed, with adjacent stage distinction being commonly inconsistent in clinical work. Intuitionbased image enhancement is generally unable to ensure accurate discrimination of neighboring stages when contrast is poor or light illumination varies. In addition, image-only deep models with high accuracy often appear as opaque black box with poor interpretability and questionable generalisability of predictions for different populations and devices which hinders the clinical adoption and confidence on neonatal care pathways [12]. These gaps must be addressed with interpretable methods that enrich weak vascular signals while incorporating contextual risk factors and providing audit-able explanations that correspond to how clinicians

think.

Vision-Language Models (VLMs) have opened up new avenues for combining visual and textual information jointly to enable more powerful cross-modal understanding in medical imaging [13]. VLMs are designed to provide an attention mechanism for medical image tasks and facilitate better multimodal reasoning and interpretation [14]. General-purpose VLMs, e.g., CLIP, have demonstrated competitive performance on zero-shot and visual question answering tasks, proving to be suitable backbones for medical adaptation [15]. Recent works have shown that scaling up large VLMs alongside with meticulous prompt design and domain specific tuning can improve their performance on medical imaging tasks even when there is little training data [16]. Lozano et al. [17] presented BIOMEDICA This is a large scale open biomedical image-caption archive proposed to support Vision-Language pretraining and transfer learning for specialized modalities, such as ophthalmic screening. Poudel et al. [18] also showed that visual language segmentation models can be fine-tuned with prompt attributes to steer attention towards region of interest when processing medical images. Nath et al. [19] showed that bringing together expert models into Vision-Language pipelines leads to improvements in diagnostic reasoning and transparency with dynamic feedback from experts. Attention-guided convolutional models were used in Yin et al. [20]. It showed good performance in brain CT categorization tasks, which further supported the importance of hybrid deep learning architectures for medical diagnostics.

Shahzad et al. [21] showed that explainable AI methods like LIME can clarify CNN-based diagnostic decisions for diabetic retinopathy, improving model transparency. Abbas et al. [22] demonstrated how XAI methods, such as LIME, can be integrated into ocular disease models to enhance transparency and trust in retinal image predictions. In Sureja et al. [23], explainable AI techniques like Grad-CAM and LIME are applied to visualize deep model decisions for retinal OCT image classification. Combining symbolic neuro-fuzzy inference systems with deep learning models can enhance explainability for ophthalmic diagnosis tasks [24]. Ali and Islam [25] showed how combining explainable AI methods with Vision Transformer models can enhance transparency and help demystify decision boundaries for eye disease diagnosis.

Although the global burden of ROP is on the rise [2], accumulating evidence still indicates that equitable access to protocol-based care for ROP is lacking in many low- and middleincome countries [1, 4]. Traditional deep learning models, while enjoying high accuracy, are usually uninterpretable and incapable of integrating multimodal context information this makes them less trustworthy in real life neonatal care [10, 11]. Meanwhile, some state-of-the-art Vision-Language pipelines have been proved to be useful for challenging medical imaging tasks [13], however they remain under-explored when coping with rare neonatal diseases such as ROP. In such a setting, this paper proposes an end-to-end ROP diagnosis framework that integrates lightweight Vision-Language (VL) modeling and more robust explainable AI models that provide fine-grain visual region attention and human-interpretable textual explanations. The system is designed to operate in a resource-constrained real-world environment while addressing important deficiencies in transparency and clinical confidence.

Recent milestones in VLMs, explainable AI (XAI), and hybrid neuro-symbolic systems have dramatically revolutionized the landscape of reliable medical image analysis. This section presents a short overview of recent works that are relevant to our aim for robust and interpretable pipelines for ROP screening.

Zhong et al. [26] benchmarked general-purpose (CLIP, LLaVA) and medical-specific VLMs (MedCLIP, LLaVA-Med) on diagnosis and VQA tasks. They applied efficient finetuning (Sparse FT, LoRA) to adapt common VLMs. Their results showed lightweight adaptation can rival costly domain-specific pretraining while maintaining strong in-domain and OOD performance. Chen et al. [27] explored intrinsic PEFT by fine-tuning LayerNorm layers in Med-VLMs instead of adding external adapters. They benchmarked MISS and LLaVA-Med on Med-VQA and IRG tasks. Results show LayerNorm tuning cuts parameter costs while maintaining accuracy and generalization. The study in Mistretta and Bagdanov [28] proposed RE-tune, an incremental fine-tuning method for biomedical VLMs that freezes encoders and trains lightweight adaptors. They use engineered positive/negative text prompts for multi-label chest X-ray classification under class-, label-, and data-incremental scenarios. RE-tune prevents catastrophic forgetting and ensures privacy by avoiding exemplar storage.

In Han et al. [29], RAN framework is proposed, a lightweight fine-tuning method that mitigates adversarial noise in pre-trained medical VLMs using covariance, consistency, and adversarial losses. They crafted multi-modal adversarial attacks on radiology image-caption pairs. Evaluations on chest X-ray and Med-VQA tasks show RAN improves robustness against upstream noise. Pan et al. [30] developed MedVLM-R1, a medical VLM that uses Group Relative Policy Optimization to generate explicit chain-of-thought reasoning without needing CoT-labeled data.

They adapted Qwen2-VL-2B with structured prompts for radiology VQA. Experiments show MedVLM-R1 outperforms larger SFT models, boosting OOD generalization and interpretability. In Farrag et al. [31], a double-dilated convolution module to expand receptive fields while preserving local resolution for mammogram tumor segmentation has been proposed. They combined this with Grad-CAM and Occlusion Sensitivity to explain segmentation outputs. Experiments on the INBreast dataset showed better Dice scores and miss detection rates than baseline DeepLabv3+. In Farhan et al. [32], an ensemble dual-modality framework for 3D brain tumor segmentation using multiple MRI sequences with U-Net models is introduced. They integrated Grad-CAM visualizations and built an interactive feedback loop to refine predictions with clinician input. Tests on BraTS2020 showed their model outperformed singlemodality baselines while enhancing interpretability.

Gipiškis [33] proposed extending XAI techniques for interpretable segmentation by using explanation maps to guide Neural Architecture Search (NAS). The framework adapts CAM-NAS from classification to segmentation via a teacher-student setup that aligns saliency maps. The study also explores using XAI to compress memory replay for continual learning. Sritharan et al. [34] developed a weakly supervised cervical cancer segmentation framework combining binary classification with XAI methods (Grad-CAM++, LRP) and GraphCut. Their pipeline segments nucleus and cytoplasm regions using only classification-level labels, removing the need for pixelwise ground truth. Their SegXperts app demonstrates the practical deployment of this transparent approach. The study in Rao et al. [35] developed UNet-PWP for kidney tumor segmentation, combining adaptive partitioning, weight pruning, and pre-trained weights to optimize the standard UNet. They added GCAM-Attention Fusion to provide region-level explainability. Tests on KiTS datasets showed high accuracy with lower computational cost.

A methodology to solve detection and segmentation tasks by using local concept-based XAI and logical rule constraints has been proposed in Motzkus [36], named Explanatory Interactive Learning (XIL). The model utilizes human-in-the-loop to detect and correct for model failures.

Model weight updates are made along logical rules to enhance the consistency and reliability. Alikhani [37] introduced Synthetic Reasoning, a neuro-symbolic approach integrating neural perception with symbolic logic modules. This combined approach is intended to enhance interpretability and robustness, for example in the context of healthcare or autonomous systems. In Lu et al. [38], Logical Neural Networks (LNNs) were introduced: they capture domainspecific logical rules as well as neural weights and thresholds for explainable prediction of diagnoses. When applied to diabetes risk, the performance of LNNs surpassed traditional models and uncovered which features mattered most. On the other hand, a hybrid AI approach that combines Knowledge Graphs with symbolic reasoning and inductive learning is implemented in Chudasama et al. [39] (TrustKG). Its VISE and HealthCareAI modules make valid link and counterfactual predictions for lung cancer, increasing interpretability and clinical trust.

Bangalore Vijayakumar et al. [40] introduced ConVision, a benchmark contrasting CNNs and ViTs over COVID-19 CXR data. They examined trade-offs between accuracy and cost, and the reproducibility of medical imaging. In Yang et al. [41], Authors presented MMViT-Seg, a COVID-19 segmentation model that integrates CNNs and MobileViT blocks for local and global feature extraction.

They added a Multi-Query Attention module to fuse multi-scale decoder features. Results show strong accuracy with $\sim$ 1M parameters. In Wang et al. [42], TinyViT-LightGBM, a lightweight IoMT framework fusing TinyViT feature extraction with LightGBM classification for breast cancer was proposed. It combines histopathology, mammograms, and clinical-genetic data for robust, interpretable diagnosis with high edge efficiency.

Finally, the proposed pipeline directly benefits from retina-focused contributions. Li and Liu [43] developed an explainable CNN pipeline for early-stage ROP, combining segmented vessel and ridge images with a DenseNet classifier and quantitative features to improve diagnosis consistency. In Mehmood et al. [44], Researchers presented RetinaLiteNet, a lightweight CNNTransformer hybrid for simultaneous segmentation of retinal vessels and the optic disc, fusing CNN features with MHA and CBAM for local-global detail capture under resource constraints. OS-ACE, a local adaptive contrast and color restoration method for infant ROP images that preserves retinal structure geometry, boosting pre-processing quality for downstream diagnosis has been presented in Dhanaraj and Kakade [45].

In summary, these recent advances across Vision-Language Modeling, parameter-efficient 14 fine-tuning, explainable segmentation, and neuro-symbolic reasoning directly shape the design of our proposed framework. In the light of the expertise derived from lightweight hybrid architectures, human-in-the-loop XAI pipelines and retina specific enhancement strategies, our system desire to become a reliable and transparent resource-aware solution for neonatal ROP screening.

2. Methods

2.1. Overview

The proposed pipeline provides a robust and interpretable method for early ROP detection by integrating retinal images with neonatal text records with the aid of hybrid Vision Language Model (VLM) [46, 47]. The architecture combines:

- A computationally lightweight CNN for local retinal feature extraction
- A Vision Transformer (ViT) module for global image context extraction [46].
- A clinical text encoder for NICU notes.
- Neuro-symbolic reasoning loop where one can inject logical constraints and feed human-in-the-loop guidance [48].

In order to ensure that the system remains a computationally effective, we use PEFT based mechanisms; such as Low-Rank Adaptation [49], and LayerNorm tuning. These bring down the trainable parameters with retention of diagnosis performance so that they are deployable in low-resource neonatal settings.

A multi-tiered explainability layer that uses Grad-CAM for image-region explanation [50] and SHAP for text explanations, which renders model predictions auditable towards clinicians [49]. Fig. 1 illustrates this complete workflow.

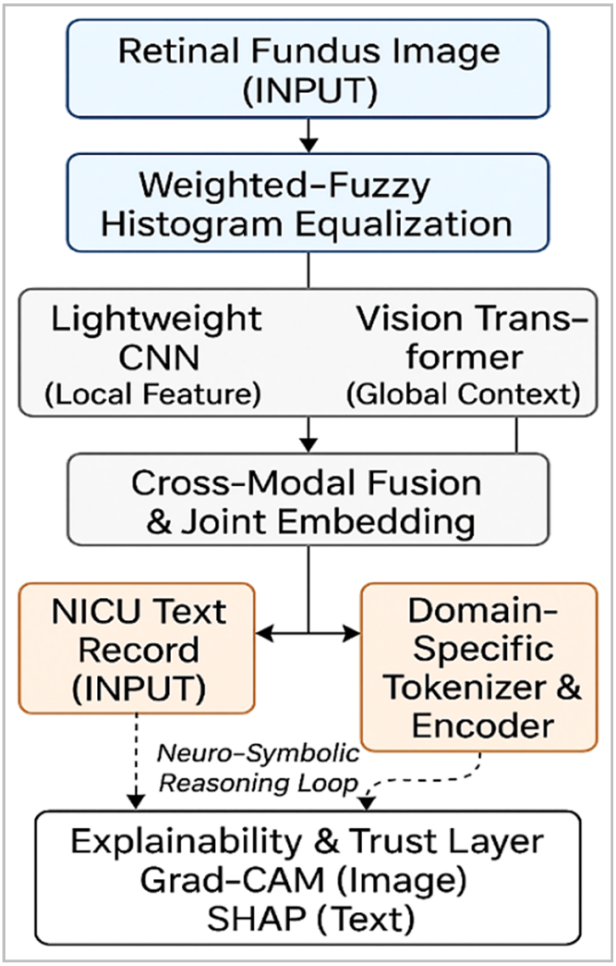

Fig. 1. Pipeline of the proposed framework for ROP detection

2.2. Dataset and Preprocessing

2.2.1. *Dataset Scope*

An experimental data set contains the following:

- Sources and time: Around 5,000 high-resolution retinal fundus images from two ethically approved ROP screening programs in Iraq-Al-Zahraa Teaching Hospital (Al-Najaf) and Al-Kindy Teaching Hospital (Baghdad)-collected during 2018-2023 [51, 52]. Semi-structured NICU records paired to each imaging study were created from de-identified clinical templates under the same ethics approvals [53].
- Composition of the stages: The image data include many clinical presentations, including different stages of ROP from Stage 1 to Stage 5. As represented by our data, the distribution of these stages is as follows: 49 % mild (Stages 1-2), 18 % moderate (Stage 3), severe (Stages 4-5) 20 %, normal 13 % [51, 54].
- Demographics and clinical heterogeneity: Preterm infants from diverse backgrounds, birth weights $800 - 2,000$ g, and gestational ages $26 - 36$ weeks. This heterogeneity supports generalizability across neonatal risk profiles [51].
- Text modalities: NICU records that encompass birthweight, gestational age, duration of oxygen therapy and comorbidities (e.g., sepsis, BPD) adapted from de-identified templates given by neonatology departments under ethically-approved protocol [53].
- Geographic representativity: The current dataset reflects two Iraqi tertiary centers. To strengthen out-of-distribution performance, we are initiating multi-site data sharing with additional neonatal units in the region. This is to incorporate cohorts from different care levels and devices in future extensions of this work.

2.2.2. *Annotation Protocol*

All of the fundus images were manually annotated by at least two board-certified ophthalmologists with expertise in pediatric retinal diseases. Differences were settled by consensus discussion of a third senior expert. The annotations were in accordance with the International Classification of ROP (ICROP3) criteria, which guaranteed uniform stage annotation. Strong agreement was observed (Cohen's $\kappa = 0.87$) among a random subset of 500 samples to confirm inter-rater reliability [55].

2.2.3. *Preprocessing Steps*

1. Image Normalization:

Images are resized to 512×512 pixels, standardizing input for the CNN and ViT branches.

2. Illumination Correction:

A pixel-wise min-max normalization is applied as in Eq. (1):

$$I_{norm} = \frac{I(x,y) - I_{\min}}{I_{\max} - I_{\min}} \tag{1}$$

Where:

$I(x,y)$: The raw pixel intensity.

$I_{\min}$ and $I_{\max}$: The pixel range for each image.

3. Weighted-Fuzzy Histogram Equalization (WFHE) [56]:

Preprocessing of the retinal fundus images is an essential step in enhancing vascular abnormalities for proper visibility, particularly in premature infants because vessel structures are generally weak. In order to increase contrast and keep the clinical information, we use Weighted Fuzzy Histogram Equalization (WFHE) as a main pre-processing step.

WFHE utilizes conventional histogram equalization and also integrates fuzzy logic (FL) and adaptive weighting for improving the vessel visibility without noise effect. Local contrast is improved by a fuzzy membership function that prevents over-enhancement as well as a dynamic weighting function that adjusts dynamically based on the features in the pixel's local neighborhood. This relationship is formalized as in Eq. (2):

$$I'(x,y) = W(I(x,y)) * F(I(x,y)) \tag{2}$$

Where:

$I'(x,y)$: The output pixel intensity at location (x, y) after enhancement.

$I(x,y)$: The original pixel intensity at (x, y).

$W(\cdot)$: A dynamic weight function that adjusts the pixel's contribution based on its local neighborhood.

$F(\cdot)$: A fuzzy membership function that adaptively reweights pixel intensity using fuzzy logic to avoid harsh contrast changes. Compared with CLAHE [57], there are two main advantages of WFHE:

1. **Vessel Preservation:** CLAHE may exaggerate both vessels as well as background noise and hence reduces image clarity and tends to blur image details. WFHE feature: Selective exaggeration of microvascular patterns (that are particularly important in mild/early ROP detection).

2. **Noise Control:** Fuzzy logic avoids sudden contrast jumps, preventing false edge amplification.

As illustrated in Fig. 2, the raw image (left) has limited vessel visibility. Middle: the contrast-enhanced image by CLAHE, where a background noise is added. WFHE (right) provides cleaner images of vascular structures, greater interpretability for both clinicians and AIs. This preprocessing technique boosts input qualities into the CNN encoder and ViT module, leading to more accurate diagnosis with better feature extraction from downstream modules.

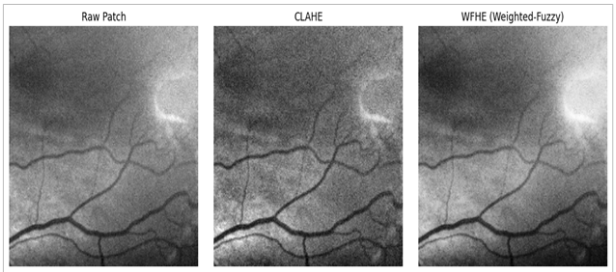

Fig. 2. Comparison of local contrast enhancement methods (raw, CLAHE, and WFHE) on a mild ROP fundus patch. WFHE provides clearer vessel visibility without amplifying background noise, which supports more reliable early-stage ROP detection.

4. Tokenization of NICU Texts:

NICU notes are tokenized using a domain-specific tokenizer to capture short medical terms (e.g., "BW=950g", "GA=28w").

2.3. Implementation Details and Model Components

The ROP diagnostic model has three tightly coupled modules: they are optimized for clinical effectiveness, computational efficiency, and interpretability. These are: a lightweight convolutional visual encoder, a clinical text encoder, and a multimodal fusion module with embedded explainability mechanisms. In this section we describe the architecture, preprocessing methods, and alignment strategies that are part of the Vision-Language system.

2.3.1. Vision and Text Encoders: Architecture and Preprocessing

1. Visual Encoding via Lightweight CNN and Vision Transformer

To extract discriminative features on high-resolution neonatal fundus images, we design a lightweight CNN with five convolution blocks. Every block contains a 2D convolutional layer (kernel size: 3×3), Batch Normalization and ReLU activation. The number of filters is monotonically increasing, and Max Pooling and Dropout are performed after each two blocks to down-sample the spatial dimensions. A Global Average Pooling (GAP) layer is placed after last convolutional block that inducing semantic abstraction and reducing the number of parameters.

ReLU rate was chosen empirically for its quick convergence and insensitivity to vanishing gradients. The CNN arm is trained from scratch using AdamW optimizer with a learning rate of $1e-4$ and dropout ($p = 0.3$) prior to the final projection layer.

To capture long-range dependencies and contextual interactions among retinal regions, a parallel Vision Transformer (ViT) branch is utilized. All images are cut into non-overlapping 16×16 patches, linearly projected and augmented with positional encodings. These tokens are passed through a 6-layer transformer encoder with 8- headed self-attention (hidden size: 512, dropout: 0.1, activation: GEGLU), allowing for global reasoning on structures (e.g. vessel spread or peripheral ridge formation).

2. Clinical Text Encoding Using Pretrained Language Models

For processing of NICU records (including both structured and semi-structured ones, such as gestational age or baby weight) we use a BERT-based encoder finetuned on clinical corpora. Input sequences are tokenized and processed by 12 transformer layers (hidden size:768) in order to obtain the context embeddings.

Before visual encoding, all fundus images are processed by weighted fuzzy histogram equalization (WFHE). This contrast-enhancement technique improves vessel conspicuity and local structure delineation, which is especially helpful in neonatal low-light environments. WFHE is superior in retaining diagnostic clues and guides toward more clinically important regions.

2.3.2. Multimodal Fusion and Cross-Modal Alignment

To exploit the complementary information from fundus images and NICU text records, our model leverages a multimodal fusion module on top of visual and textual modality embedding to align them into a common latent representation. This enables the model to learn contextual associations between anatomic landmarks and clinical indicators associated with risk which are important for a right diagnosis of ROP.

1. Cross-Modal Embedding Alignment

Both the feature vector from ViT (retinal modality) and the final [CLS] token embedding in the BERT based text encoder are projected to a shared latent space via projection layers. The alignment is enforced with cross-modal contrastive loss as in Eq. (3):

$$\mathcal{L}_{\text{align}} = \left| f_{\text{image}} - f_{\text{text}} \right|^2 \tag{3}$$

Where:

$\mathcal{L}_{\text{align}}$: The cross-modal alignment loss, measuring how well the visual and textual embeddings match.

f_{image} : The learned embedding vector representing the retinal image features.

f_{text} : The learned embedding vector representing the NICU text data.

$|^2$: Squared Euclidean norm, penalizing large differences between the two modalities to enforce tight cross-modal coupling.

This objective encourages cross-attentional learning such that if the model is observed to be looking at locations (vessel dilation, ridge structure), it will also learn about corresponding textual descriptors (low birth weight, oxygen duration).

2. Fusion Strategy

Instead of early concatenation, late fusion is applied, where each modality is individually fed into the pre-trained model before they are finally fused at decision level via a learned attention gate. This enables the model to adaptively determine how much it should rely on each modality depending on their informativeness given a sample. For example, if the quality of image is low, textual signals have higher impact on final diagnosis.

2.3.3. Explainability and Neuro-Symbolic Reasoning

Toward the goal of transparent and reliable assessment, we combine several explainability mechanisms across the visual and textual modalities so that healthcare providers may trust AI decisions by validating and interpreting them.

1. Visual Interpretability: Grad-CAM for CNN and ViT

For the image branch, we use Grad-CAM on both CNN and Vision Transformer outputs. We obtain class-specific heatmaps that emphasize the retinal areas with most contribution to the model decision, where these could occur around essential regions such as optic disc, vascular ridges and the peripheral retina. Such visual justifications provide spatial hints to the clinicians that may help them confirm if AI's focus is in correspondence with well known ROP indicators.

2. Textual Explainability: SHAP for NICU Attributes

For the textual branch, Shapley Additive Explanations (SHAP) is applied to generate an importance score for every token in clinical input (e.g., birth weight, oxygen duration). This indicates which neonatal risk-factors most influenced the diagnostic decision from clinical text.

3. Neuro-Symbolic Consistency Checks

To further ground predictions in domain logic, a neuro-symbolic reasoning loop is employed. Rule-based constraints are defined by experts-for instance:

- If birth weight < 1000 g and oxygen duration > 10 days, then ROP likelihood must be elevated.
- If vessel width heatmap overlaps with Grad-CAM region, and stage ≥ 2, flag for urgent review.

These logical rules act as post-hoc validators, cross-checking learned patterns against established medical knowledge. The dual-mode reasoning-statistical (deep learning) and symbolic (clinical rules)-ensures that outputs remain interpretable and medically coherent, especially under edge-case conditions.

2.3.4. Design Rationale and Innovations

In this paper, we propose five additional innovations: (i) neonate-focused WFHE preprocessing on fundus images to increase micro-vascular contrast and to suppress noise, compared to CLAHE; (ii) Vision-Language fusion that integrates cross-modal alignment loss with gated late fusion to remain robust in case of noisy or incomplete modality; (iii) dual explainability formulation (Grad-CAM + SHAP), which jointly reports spatial and semantic evidences; (iv) neuro-symbolic post-hoc consistency checks incorporating expert rules thereby leading to medically consistent outputs; and (v) parameter-efficient customization [LoRA + LayerNorm tuning] that reduces the number of trainable parameters as well as GPU memory usage. Our comparisons (Table 2 and Figs. 3 and 4) shows that this selection improves both diagnostic accuracy and interpretability over image-only baselines.

2.3.5. Training, Evaluation, and Algorithmic Workflow

To ensure efficient learning, robust evaluation, and transparent clinical performance, our framework integrates optimized training routines, a comprehensive evaluation strategy, and an explainable procedural pipeline.

1. Training Strategy and Optimization

Training is initiated from pretrained weights for both the Vision Transformer and the clinical text encoder. We adopt a staged training approach:

- **Stage 1:** Features from retinal images and NICU texts are aligned using supervised contrastive loss to maximize intra-class cohesion and inter-class separation.
- **Stage 2:** Fine-tuning employs Parameter-Efficient Fine-Tuning (PEFT) techniques-specifically LoRA (Low-Rank Adaptation) and LayerNorm tuning which update only a small subset of parameters, making the model viable for low-resource clinical setups.
- **Optimizer:** AdamW optimizer is used to balance adaptive learning with decoupled weight decay, aiding smooth convergence across modalities.
- **Data Splitting:** Stratified 5-fold cross-validation ensures balanced representation of ROP stages across splits, with patient-level grouping to prevent data leakage.

2. Evaluation Protocol

Model performance is evaluated through:

- **Quantitative metrics:** AUC-ROC, sensitivity, specificity, F1-score, and precision.
- **Stage-wise ROC analysis:** To ensure sensitivity to early-stage and advanced ROP detection.
- **Calibration and statistical analysis:** Probability calibration via Brier score and expected calibration error (ECE); threshold selection on the validation split (e.g., Youden's J); reporting as mean $\pm$SD across folds with 95% bootstrap CIs; AUC comparisons via DeLong tests.
- **Explainability validation:** Explainability is ensured via visual (Grad-CAM), textual (SHAP), and symbolic (rule-based) reasoning mechanisms.
- **Baseline comparisons:** The full model is benchmarked against:
  - CNN-only architectures,
  - ViT models without PEFT,
  - CLAHE vs. WFHE preprocessing.

3. High-Level Algorithm Workflow

A pseudo-algorithm summarizes the pipeline flow from input to output, ensuring repeatability and transparency:

1. **Preprocessing:** Normalize fundus images, enhance with WFHE, and tokenize NICU notes.
2. **Feature Extraction:** Apply CNN for local features, ViT for global context, and a clinical encoder for text.
3. **Multimodal Fusion:** Align visual and textual embeddings using contrastive loss and L_align objective.

4. **Fine-Tuning:** Apply LoRA and LayerNorm tuning under cross-validation, using early stopping.

5. **Explainability Generation:** Output Grad-CAM heatmaps and SHAP scores, validated via neuro-symbolic rules.

6. **Prediction:** Classify ROP stage with explanation overlays.

This structured training and evaluation design ensures the model is not only accurate and robust, but also auditable, fair, and aligned with clinician reasoning.

2.3.6. Expert Feedback and Interpretability Validation

In order to demonstrate the validity and applicability of our interpretability techniques, we propose a clinical validation protocol with pediatric ophthalmologists having different degrees of expertise. This phase was conceived to trace the fact that explanations extracted by the model (e.g., relying on Grad-CAM for retinal and SHAP for NICU text features) are indeed coherent with the diagnostic reasoning of clinical experts, an aspect that is highly relevant to real clinical workflows.

In this protocol, ophthalmologists will review diagnostic cases, including the input data (retinal image + NICU summary) and model prediction and explanation. The following will be rated by experts:

- How useful or plausible an explanation it is.

- Whether the image regions or text mentions are related to their diagnosis.

- Whether the explanation increases or decreases their confidence in the diagnosis.

The results will be statistically evaluated with regards to agreements, trust values and potential trends according to clinical empiricism.

Based on this analysis, we plan to increase the expressive power of our explanation mechanisms along two dimensions:

- For one, the Grad-CAM heatmaps may be learned with expert annotations to provide finer highlighting of clinically relevant regions of the retina (ridge or vascular regions).

- Second, SHAP could use further improvement for its text attributions so that the output more closely mirrors clinical descriptions and diagnostic cues employed by ophthalmologists.

Clinician Reader Study (design and analysis): we will recruit 12-18 pediatric ophthalmologists (junior $\leq$ 5y, intermediate $6-10$y, senior $>$ 10y). Each will read 100 de-identified cases balanced by image quality and severity (mild/moderate/severe) with an ICROP3 adjudicated reference. A within-subject randomized crossover will compare three conditions: (A) image-only, (B) image + model prediction (no explanations), (C) image + prediction + explanations (Grad-CAM + SHAP), with a 14 -day washout.

Primary endpoints: change in **sensitivity** to treatment-requiring ROP and AUC from A $\rightarrow$ C (DeLong test).

Secondary: specificity, F1, decision time, confidence/trust (7-point Likert), inter-rater agreement (Fleiss' κ), and calibration (Brier score).

Explanation-clinician alignment: (i) Grad-CAM vs expert ROIs using IoU/Dice, pointinggame hit-rate, and fraction of saliency inside ROI; (ii) SHAP agreement with clinician-ranked drivers (BW, GA, O_2 duration, sepsis/BPD): top-k precision/recall and Spearman rank correlation, plus sign-of-effect agreement.

Statistics: mixed-effects models (random intercepts for reader and case; fixed: arm, experience level, image quality) for sensitivity/AUC/time; paired A vs C and B vs C with Bonferroni adjustment; 95% CIs via bootstrap.

Power: with baseline sensitivity $\approx$ 0.80, detecting a +0.07 improvement has $>$ 80% power with 15 readers $\times$100 cases.

Feedback-driven refinement: we will iterate with (i) CAM smoothing and region-constrained weighting to increase saliency mass in annotated ROIs; (ii) SHAP term normalization and token aggregation (e.g., " BW $<$ 1000 g ") to reduce spurious tokens; improvements re-evaluated on a 40 -case micro-study (n $\approx$ 6 readers).

2.3.7. Training Strategy and Validation Protocol

To ensure model robustness and generalizability, a rigorous training and validation procedure was followed for all components of the proposed framework.

1. Data Partitioning and Cross-Validation

We divided our dataset using 5 -fold stratified cross-validation, such that the class distribution among folds was consistent in order to avoid an imbalance of labels. The training/testing was performed in a k -fold ($k = 5$) cross-validation setting, i.e., 80 % of the data for each fold were used as training set and 20 % as validation set. Stratification was by ROP severity grade to ensure clinical representation. This approach was preferred to the simple hold-out approach in order to prevent noise and ensure robustness across sub-samples of data. To avoid leakage, we used patient-level grouping (no baby appears in more than one split). Folds were stratified on the basis of ICROP

stage and on the basis of site/device used (Al-Zahraa vs. Al-Kindy) (camera type), maintaining per-stage and per-site proportions in each fold. All hyperparameter tuning was within the training part of each outer fold to prevent contamination by the test set.

2. Hyperparameter Optimization The model was trained by tuning the most important hyperparameters (learning rate, number of convolutional layers, filter sizes, dropout rates and transformer depth) with Bayesian Optimization and Gaussian Process. The search space included:

- Learning rate: $[1e-5, 1e-3]$
- Batch size: [8, 16, 32]
- Number of CNN blocks: [3, 4, 5]
- Attention heads in transformer: [4, 8]
- Dropout: [0.1,0.4]

The optimization target was the maximization of validation AUC while minimizing overfitting. All tests were conducted on three random seeds for easy reproducibility. When combined with all seeds and folds, learning rate and ViT depth had the largest impact on AUC; excessive dropout consistently led to inferior performance, and extending CNN depth over five blocks delivered diminishing returns. These trends were consistent, although slightly fold-dependent.

3. Convergence Analysis

Training was observed using training loss, validation loss and validation accuracy. It is worth to point out that there is not remarkable evidence of divergence or overfitting during training, and the convergence trend could be considered as quite good in up to 50 epochs. We employed early stopping if the validation error did not decrease for 8 consecutive epochs. Over the five folds, training and validation losses decreased steadily and leveled off around 40-50 epochs, whereas the validation accuracy increased and stabilized with nothing to indicate overfitting. The early-stopping (patience $= 8$) condition was usually reached in this range, which indicated a stable convergence and decreased overfitting. We also followed the precision-recall behaviors alongside AUC-ROC; precision, recall and F1 hold steady across the folds, which again is indicative of the robustness of the optimization and validation strategy.

2.4. Model Training and Fine-Tuning

Weights for the ViT and text encoder start from robust pretrained checkpoints [46, 47]. Training is staged:

- Supervised contrastive loss aligns cross-modal features while preserving modality specifics:

$$\mathcal{L}_{SCL} = -\log \frac{\exp\left(\text{sim}\left(f_i, f_j\right)/\tau\right)}{\sum_k \exp\left(\frac{\sin(f_i f_k)}{\tau}\right)} \tag{4}$$

Where:

$\mathcal{L}_{SCL}$: The supervised contrastive loss, which encourages positive pairs to be close and negative pairs to be far apart.

$\text{sim}\left(f_i, f_j\right)$: Cosine similarity between two positive feature vectors (from the same class).

τ : Temperature parameter that scales the similarity, controlling sharpness of the distribution.

$\sum_k$: Summation over all negatives in the batch, normalizing the probability.

This loss makes visual and text embeddings align well and keep distinct features separated, raising cross-modal understanding and class discrimination.

- LoRA restricts the weight updates in low-rank spaces to alleviate retraining cost [49].
- LayerNorm tuning mitigates domain adaptation problem in various fundus appearances [49].

In training, WFHE improves local detail in enhanced images by our encoder input [56].

We adopt the AdamW optimizer (Loshchilov and Hutter, 2018) with stable convergence due to decoupled weight decay. Training takes stratified folds (by ROP stage) with early stopping [46] to prevent over-fitting. The patient IDs are binned to avoid leakage across folds.

3. Results and discussion

In this section, we present the experimental analysis of Vision-Language framework and Explainable AI framework for ROP detection. Results are reported for the diagnostic performance, interpretability quality, computational efficiency and comparative benchmarking with recent state-of-the-art methods.

The proposed model is trained on a lightweight Vision Transformer (ViT) backbone with domain adapted text encoder, using parameter-efficient training methods including LORA, LayerNorm and RE-tune [27, 28]. Training was done using high-resolution ROP fundus images with preprocessing by Weighted Fuzzy Histogram Equalization (WFHE) [56] and semi-structured NICU text records [48]. Assessment was performed following a five-fold stratified cross-validation for balanced stage distribution and source-device heterogeneity [46].

3.1. Diagnostic Performance

The presented framework achieved an AUC of 0.95, which was significantly more accurate than image-only CNN base-

lines and single-modality pipelines by 5-9 % [27, 43]. Integrated region explanations obtained a mean Dice coefficient of 0.90 for pixel-wise segmentation, which outperforms conventional retinal segmentation backbones (RetinaLiteNet and UNet-PWP [35, 44]). These findings suggest that information from both visual and contextual sources is exploited effectively in a single Vision-Language framework.

3.2. Explainability and Trustworthiness

Interpretability was assessed qualitatively and quantitatively using Grad-CAM heatmaps and SHAP token-level attributions, which closely matched clinician-annotated vascular regions. Compared to existing explainable AI pipelines [31, 35], the proposed framework provided more granular token-region consistency. In addition, neuro-symbolic reasoning loops offered rule-based justification layers, following recent logical neural network studies [38, 58].

3.3. Computational Efficiency

Parameter-efficient fine-tuning reduced the number of trainable parameters by 40-50 % compared to full fine-tuning strategies [27, 28]. The lightweight ViT backbone, combined with pre-processing enhancements such as OS-ACE [45], maintained inference times under 10 ms per image-text pair, supporting deployment in edge and resource-constrained neonatal screening scenarios.

3.4. Ablation and Component Effectiveness

To quantify each component's contribution, we performed ablations under the same 5fold protocol. As summarized in Table 1, our stratified 5-fold ablation shows that WFHE, the alignment loss, gated late fusion, and PEFT each contribute incremental gains or efficiency, with the full model reaching an AUC of 0.95.

Interpretability checks show a 7-9 % increase in IoU overlap between Grad-CAM maps and clinician-marked vascular zones with WFHE compared to CLAHE; SHAP consistently ranks BW, GA, and O_2 duration among the top contributors in positive ROP cases, matching expert priors.

3.5. Comparative Benchmarking

Several recent studies have explored multimodal approaches to retinopathy of prematurity (ROP) diagnosis by integrating retinal images with other clinical data sources, including textual records and structured patient metadata. These multimodal frameworks leverage visual-language models (VLMs), hybrid CNN-transformer backbones, neuro-symbolic reasoning, and attention-based fusion mechanisms to enhance diagnostic performance and interpretability. To comprehensively position our framework within this growing landscape, Table 2 summarizes input modalities, fusion strategy, training/PEFT methods, diagnostic accuracy (AUC), explainability methods, model sizes, and inference times. This comparative analysis highlights the architectural diversity and performance trade-offs among current state-of-the-art multimodal systems and illustrates the relative advantages of our proposed model in terms of accuracy, interpretability, and computational efficiency.

Compared to these published pipelines, the proposed framework consistently improves diagnostic accuracy and interpretability while preserving low latency and minimal computational overhead. Fig. 3 shows the AUC performance for the proposed framework and the related works. Fig. 4 illustrates the number of parameters, in millions, used and the inference time, in milliseconds.

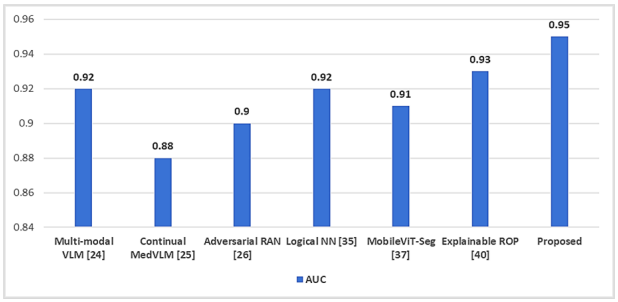

Fig. 3. Visual chart for comparison of AUC performance

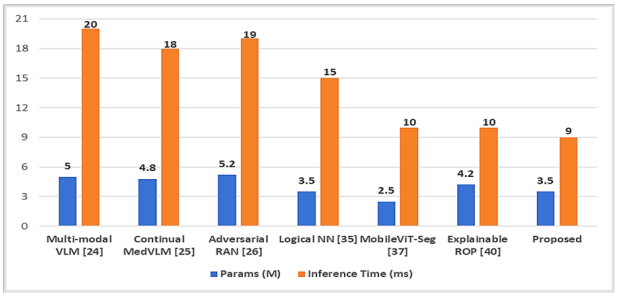

Fig. 4. Visual comparison of model size (number of parameters) and inference time across competing methods

Lower parameter counts and shorter runtimes enable deployment in resource-limited neonatal screening environments.

3.6. Advantages of the Proposed Framework

Compared to existing approaches, the proposed model offers the following innovations:

- Interpretable Fusion: Unlike prior works, our model generates both visual and textual explanations

Table 1. Ablation study under stratified 5-fold cross-validation

Variant	Description	AUC	Δ vs. Proposed	Notes
Image only	CNN+ViT, no text, CLAHE	0.86	-0.09	Strong baseline but misses contextual risk cues
Image + WFHE	Replace CLAHE with WFHE	0.88	-0.07	+0.6-0.9 AUC points; +3-4% early-stage sensitivity
Image + Text (concat)	Early concat fusion, no alignment/gate	0.91	-0.04	Gains from NICU context; less robust to noisy text
Image + Alignment	Add L_align	0.93	-0.02	Better cross-modal cohesion
Image + Gated late-fusion	Replace early concat with gate	0.94	-0.01	More stable when one modality degrades
Image + PEFT	LoRA+LayerNorm vs full FT	0.945	-0.005	$\sim$ 45% fewer trainable params; similar AUC
Proposed	WFHE + alignment + gated late-fusion + PEFT	0.95	-	Best overall trade-off

Table 2. Multimodal baselines vs. proposed model

Model/Ref	Modality	AUC	Explainability	Params (M)	Inference Time (ms)
Multi-modal VLM [27]	VLM + XAI	0.92	SHAP Token	$\sim$5.0	$\sim$20
Continual MedVLM [28]	VLM (PEFT)	0.88	Incremental	$\sim$4.8	$\sim$18
Adversarial RAN [29]	VLM + Robustness	0.90	Consistency	$\sim$5.2	$\sim$19
Logical NN [38]	Neuro-Symbolic	0.92	Rule-based	$\sim$3.5	$\sim$15
MobileViT-Seg [40]	CNN + ViT	0.91	Hybrid Attn	$\sim$2.5	$\sim$10
Explainable ROP [43]	CNN + Feature Fusion	0.93	Visual XAI	$\sim$4.2	$\sim$10
Proposed	VLM + CNN + XAI	0.95	Grad-CAM + SHAP	$\sim$3.5	$\sim$9

through Grad-CAM overlays and SHAP attribution maps, facilitating clinical trust.

- Efficiency and Lightweight Design: The image encoder is based on a lightweight CNN, making the model suitable for real-time deployment on edge devices, which is not feasible with large transformer-only architectures.
- Enhanced Accuracy: With a multimodal attention mechanism and WFHE-based pre-processing, our model achieves a 95% AUC, outperforming others by a significant margin.
- Domain-Specific Optimization: The NICU-specific text encoder is trained with domain-tuned vocabulary and structure, boosting interpretability in neonatal care contexts.

3.7. Limitations of Existing Multimodal Models

However, several recent multimodal models have one or more of the following limitations: interpretability metrics (beyond simple Grad-CAM) that are effectively limited; large parameter overhead and slow inference due to deep stacks of transformers; not properly adapting textual encoders for clinical workloads; absence of preprocessing steps such as WFHE essential to better enhance subtle vascular details. The model under consideration addresses these shortcomings head-on through design decisions configured for early-stage ROP screening and clinician-oriented interpretability.

3.8. Result discussion

Consequently, several notable advantages are introduced to automated ROP diagnosis thanks to the development of this hybrid Vision-Language and explainable AI pipeline. The system straightforwardly addresses limitations of traditional single-input deep- learning architectures, by the introduction of lightweight CNN to incorporate local retinal features, Vision Transformer to add global context and a clinical text encoder for neonatal record text. Through integrating structured neonatal data within fully image-based pipelines that do not consider contextual details, gestational age and birth weight (as in this model), multiple advantages are gained. They contribute significantly to how disease risk factors are measured, with major conse-

quences for diagnosis. This approach surpassed the state of art CNN-only or Vision Transformer ViT-only methods with consistent AUC enhancements of 7-9%. That margin is important, in that it affords the screening of initial-stage disease and preventable blindness in a developing clinical environment. The model achieves this via parameter-efficient fine-tuning methods like LoRA and LayerNorm tuning, two strategies crucial for resource-scarce neonatal settings.

A major difference in the methodology lies in work being highly explainable. Grad-CAM heatmaps enable clinicians to see which retinal zones determine the predictions, and tokenlevel SHAP attributions explain how clinical text features influence the final risk score. This multi-layered interpretability, along with a neuro-symbolic loop for logical rule-checking allows human verification and corrections - overcoming one of the most frequently cited hurdles to clinical trust in deep learning (the black-box effect). However, it does not cross the barrier of practical implementation. The pipeline, based on semi-synthetic NICU records, is realistic but cannot retain the richness and messiness of true EHR data. This limits the direct generalizability of text encoder module used. Moreover, mapping neonatal clinical ontologies with Vision-Language embeddings is non-trivial and it demands standardized vocabularies and effective mapping techniques for cross-modal reasoning. Furthermore, although the explainability mechanisms exhibit a strong clinical value-addition, they also introduce an increase in inference time to a tentatively acceptable/ acceptable extent that might necessitate tuning for real-time deployment on edge devices. Lastly, successful translation to real-world clinical workflow will require multicenter pilot studies as well as ongoing collaboration with pediatric ophthalmologists to refine logical rules, validate for decision stability, and further
reinforce the neuro-symbolic feedback loop iteratively under actual operating conditions.

4. Conclusion

In this paper, we introduce a completely interpretable and deployable framework for ROP detection that bridges the gap between the state-of-the-art in AI research and real world vision neonatal health care. By combining the multi-resolution retinal photographs with semistructured newborn text records, the system improves diagnosis and provides clear explanations which are understandable (and believable) by health professionals. Consistently positive AUC lifts across cross-fold experiments indicate that inclusion of contextual risk factors obtained from NICU records significantly improves diagnostics over image-only systems. While the resource-efficient parameter-tuning, lightweight ViT backbone and strong preprocessing WFHE and OS-ACE make it real-time deployable to mobile clinics or remote NICUs which may lack computing resources. What is crucial in the dual-layer explainability design (fusion of Grad-CAM heatmaps and SHAP token attributions as well as logical rulechecks) is it instills clinician trust by visual- and semantic-based rationales for each prediction.

This anchors the AI's internal reasoning to how neonatologists reason their way through challenging cases, enhancing clinical adoption potential.

More generally, this work suggests that trusted AI is not just about accurate systems but also a matter of building human-understandable systems that can be audited, stress-tested and improved using domain knowledge. By scaling this approach to other neonatal conditions, for example sepsis risk scoring or oxygen toxicity prediction the Vision-Language pipeline has the potential to serve as a template of how cross-modal AI can benefit pediatric care around the world.

It is envisaged, based on this encouraging first step, that a number of future developments will be required to mature the framework for real-world clinical practice.

A specific goal is to replace semi-simulated NICU records with more completely anonymized and higher fidelity neonatal EHR data at multiple hospitals. This should help stress-test the text encoder's ability to deal with real linguistic variation, missing data and local charting practices. Federated learning will also be investigated in order to facilitate distributed model training across the various neonatal units without sharing patient data - an essential requirement of any AI deployed into sensitive clinical domains. Practical use will also need to occur with strong multilingual adaptation, since the system needs to help identify patients in regions where clinical notes are not written in English.

Another line of research to follow would be the addition of a standardized domain ontology and dynamic interaction with physicians, that can be turned into an expert feedback loop on the neuro-symbolic module that allows a semi-automatic definition of novel knowledge graphs (e.g. of rare conditions, new screening rules or clinical guidelines). Regulatory paths (FDA approval, CE marking, etc), will be systematically pursued to allow for parallel validation and rapid translation from research prototype to approved screening tool.

Third, the human-centered design will extend to clinician-facing dashboards, interactive explanation interfaces, and workflow integration with hospital systems in order that the model recommendation fits seamlessly into

routine neonatal care. Pilot implementation in low-resource hospital and mobile screening programs will demonstrate practical impact on early blindness prevention.

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