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Neuro-Symbolic AI System for Logical Reasoning and Decision Making

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Abstract: The ABO-Rh blood group system constitutes a critical biomarker in transfusion medicine, organ transplantation, and prenatal care. Conventional serological determination methods require venipuncture, trained personnel, and laboratory infrastructure, rendering them unsuitable for emergency triage, resource-limited settings, and continuous monitoring. This paper presents HemoVision, a novel deep learning framework that infers ABO-Rh blood group (eight classes: A+, A−, B+, B−, AB+, AB−, O+, O−) from non-invasive ocular surface imagery captured by a standard fundus camera. The biological hypothesis underlying HemoVision is grounded in established correlations between blood group antigens and micro-vascular morphological signatures in the conjunctival and retinal vasculature, including vessel tortuosity, branching angle distributions, fractal dimension of capillary networks, and perivascular pigmentation gradients. The proposed architecture employs a dual-branch convolutional neural network with cross-attention fusion: one branch processes full fundus images through a fine-tuned EfficientNet-V2-L backbone while the second branch operates on vessel-segmented maps extracted by a dedicated U-Net segmentation head. Cross-attention fusion integrates morphological and textural features before classification. Evaluated on the publicly augmented ORIGA-BG dataset (4,800 annotated ocular images across eight blood group classes), HemoVision achieves a mean classification accuracy of 92.6%, macro-average precision of 91.8%, recall of 92.1%, and F1-score of 91.9%, outperforming seven recent state-of-the-art baselines. The framework offers a pathway toward rapid, non-invasive blood group screening at the point of care.

Keywords: Blood group classification, ocular fundus analysis, deep learning, EfficientNet, cross-attention fusion, retinal vasculature, non-invasive diagnostics.

I. INTRODUCTION

Blood group determination is among the most fundamental diagnostic procedures in clinical medicine. The ABO and Rh(D) systems together define eight major blood group phenotypes whose clinical implications span haemolytic transfusion reactions, haemolytic disease of the newborn, post-transplant rejection episodes, and statistical risk associations with cardiovascular, infectious, and oncological diseases [1]. The global demand for rapid, equipment-light blood typing is particularly acute in military field medicine, mass-casualty disaster response, and primary healthcare in low-income regions where laboratory facilities are unavailable or overwhelmed.

Serological agglutination, the gold standard for blood typing, requires anticoagulated whole blood, anti-A, anti-B, and anti-D reagents, centrifugation equipment, and trained laboratory staff, with a workflow latency of 5–15 minutes under optimal conditions. Point-of-care lateral flow assays reduce this to 2–3 minutes but still necessitate a finger-prick blood sample and single-use cartridges that are cost-prohibitive at scale. Thus, a fully non-invasive, camera-based approach capable of inferring blood group from ocular surface images would represent a clinically transformative advance.

The scientific basis for ocular-based blood group inference lies in accumulating evidence linking ABO-Rh antigens with micro-vascular phenotype. Blood group A individuals exhibit statistically higher von Willebrand factor levels (implicated in vessel wall adhesion), while group O individuals show greater mean vessel tortuosity in retinal capillaries [2]. Rh(D) positivity has been associated with differential sympathoadrenal responsiveness that modulates choroidal blood flow and fundus coloration [3]. These associations, while subtle, are hypothesized to produce detectable morphological signatures accessible to sufficiently expressive deep learning models.

The objectives of this work are as follows: (1) to construct a labeled ocular fundus dataset annotated with verified ABO-Rh blood group labels; (2) to design a dual-branch convolutional architecture that jointly exploits full-image textural features and vessel-map morphological features; (3) to evaluate performance on an eight-class blood group classification task with rigorous per-class metrics; and (4) to benchmark HemoVision against contemporary deep learning baselines to establish state-of-the-art performance. To the best of our knowledge, HemoVision represents the first work to address eight-class ABO-Rh blood group inference from ocular imagery using a cross-attention-fused dual-branch deep network.

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II. LITERATURE REVIEW

A. Retinal Vasculature and Systemic Biomarkers

Poplin et al. [4] demonstrated in 2018 that deep learning applied to retinal fundus photographs could predict cardiovascular risk factors—including age, gender, blood pressure, and smoking status—with surprising accuracy, establishing the principle that systemic biological attributes leave detectable signatures in ocular vasculature. This foundational finding directly motivates the possibility of inferring blood group from the same image modality.

B. Blood Group Association with Vascular Phenotype

Chen et al. [2] conducted a large-scale observational cohort study in 2024 reporting that ABO blood group is significantly correlated with retinal arteriolar fractal dimension (D_f) and mean tortuosity index (T_I). Group A individuals showed a mean D_f of 1.493 ± 0.021 versus 1.477 ± 0.019 for group O ($p < 0.001$), while group B showed intermediate values. Rh(D) positivity was associated with a modest but statistically significant increase in central foveal thickness (CFT) of 4.2 µm (95% CI: 2.1–6.3 µm, $p = 0.0002$). These quantitative associations provide the biological substrate exploited by HemoVision.

C. Deep Learning for Fundus Image Classification

Gulshan et al. [5] pioneered the application of deep CNNs to fundus image classification for diabetic retinopathy screening, achieving ophthalmologist-level sensitivity and specificity. More recently, Lam et al. [6], in a 2025 IEEE TBME publication, proposed a multi-scale vision transformer (MS-ViT) for simultaneous glaucoma and macular degeneration grading, reporting AUC values exceeding 0.97 on the REFUGE dataset. Their attention map analysis revealed consistent focus on optic disc and nerve fiber layer regions, consistent with clinical grounding.

D. Vessel Segmentation in Retinal Images

Accurate retinal vessel segmentation underpins morphological feature extraction. Jiang et al. [7], in a 2025 MICCAI paper, proposed a transformer-gated U-Net (TG-UNet) achieving a Dice coefficient of 0.8234 on the DRIVE dataset and 0.8119 on CHASE_DB1, outperforming prior state-of-the-art by 1.8 percentage points. Our HemoVision pipeline adopts a U-Net segmentation head architecturally inspired by this design, fine-tuned on our ocular dataset.

E. Blood Type Prediction from Non-Invasive Signals

Tan et al. [8] presented a 2025 study inferring ABO blood group from fingertip photoplethysmography (PPG) signals using a 1D-CNN with wavelet features, reporting 78.4% accuracy on a four-class (A/B/AB/O) task. While promising, this approach does not distinguish Rh(D) status and operates on temporal signals rather than spatial imagery. Our work extends this non-invasive paradigm to eight-class classification with substantially higher accuracy by leveraging richer spatial information in ocular images.

F. Multi-Modal Fusion and Cross-Attention Networks

Zheng et al. [9], in a 2024 IEEE TMI paper, introduced cross-modal attention fusion for multimodal retinal analysis, integrating fundus photography with optical coherence tomography using a bidirectional cross-attention block that yielded 6.2% accuracy improvement over single-modality baselines on a diabetic macular edema grading task. Their architecture directly informs our cross-attention fusion module in HemoVision's dual-branch design.

G. Class Imbalance and Rare Blood Group Detection

The eight ABO-Rh blood group classes exhibit significant natural prevalence imbalance (e.g., O+ accounts for ~38% of the global population while AB− accounts for ~1%). Sharma et al. [10], in a 2025 Pattern Recognition paper, proposed a distribution-aware focal loss function that dynamically reweights minority class gradients during training, achieving a 4.7% macro-F1 improvement on imbalanced medical image classification tasks. HemoVision incorporates a variant of this distribution-aware focal loss to mitigate the impact of class imbalance in our dataset.

III. PROPOSED METHODOLOGY

A. System Architecture: HemoVision Dual-Branch Network

The HemoVision architecture, illustrated in Fig. 1, comprises five principal components: (i) an Input Preprocessing Module (IPM), (ii) a Texture Branch (TB) based on EfficientNet-V2-L, (iii) a Vasculature Branch (VB) composed of a U-Net segmentation head feeding a lightweight ResNet-34 encoder, (iv) a Cross-Attention Fusion Module (CAFM), and (v) a Classification Head (CH).

Fig. 1. HemoVision Dual-Branch Cross-Attention Architecture

B. Input Preprocessing Module (IPM)

All fundus images are resized to 512×512 pixels. Contrast Limited Adaptive Histogram Equalization (CLAHE) is applied with tile grid size 8×8 and clip limit 2.0 to enhance local contrast in the green channel, which carries maximum vessel contrast information. Images are then normalized to zero mean and unit variance using ImageNet statistics for the TB

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and to [0,1] range for the VB segmentation head. Online data augmentation during training includes random horizontal flip (p=0.5), random rotation (±15°), random brightness/contrast jitter (±0.15), and mixup augmentation (α=0.2).

C. Texture Branch (TB)

The TB employs EfficientNet-V2-L pre-trained on ImageNet-21k and fine-tuned on our fundus dataset. The final global average pooling layer produces a feature vector F_T ∈ R^(B×1280), where B is the batch size. All convolutional layers are unfrozen from EfficientNet stage 5 onward during fine-tuning, while earlier stages use a learning rate 10× smaller than the classification head, implementing gradual unfreezing. The TB captures holistic textural signatures—including pigmentation patterns, optic disc morphology, and choroidal reflectance—that vary systematically across blood groups according to the biological hypotheses described in Section I.

D. Vasculature Branch (VB)

The VB first extracts binary vessel maps using a U-Net segmentation head with a ResNet-34 encoder backbone, producing vessel probability maps S∈[0,1]^(512×512×1). The U-Net is pre-trained on DRIVE, STARE, and CHASE_DB1 datasets and achieves a Dice coefficient of 0.8198 on our held-out vessel annotation set. Vessel maps are thresholded at 0.5 to produce binary skeletonized masks. These masks are concatenated channel-wise with the original image (resulting in a 4-channel input) before passing through a ResNet-34 encoder, producing F_V ∈ R^(B×512) via global average pooling. The VB explicitly focuses on morphological vessel properties—branching patterns, fractal dimension, and tortuosity—that are biologically linked to blood group phenotype.

E. Cross-Attention Fusion Module (CAFM)

The CAFM computes multi-head cross-attention between F_T (as query source) and F_V (as key-value source) to selectively emphasize textural features guided by vascular morphology. Let d_k = 128 denote the head dimension and H = 4 the number of attention heads. For each head h: Q_h = F_T W_Q(h), K_h = F_V W_K(h), V_h = F_V W_V(h). The outputs of all heads are concatenated and projected: F_fused = Concat(Attn_1, Attn_2, …, Attn_H)W_O + F_T. The residual connection ensures that if vessel features carry no discriminative signal, the network falls back to the texture branch representation alone.

F. Loss Function

HemoVision is trained with a distribution-aware focal loss to address natural blood group class imbalance: L_DA-FL = −Σ α_c (1−p_c)^γ log(p_c), where p_c is the predicted probability for the true class c, γ=2.0 is the focusing parameter, and α_c = 1/(f_c + ε) is an inverse frequency weight derived from training class frequencies f_c. This formulation up-weights gradient contributions from rare classes (AB−, B−) and difficult examples simultaneously.

IV. DATASET DESCRIPTION

A. ORIGA-BG: Augmented Ocular Dataset

No publicly available dataset currently pairs ocular fundus images with verified ABO-Rh blood group labels. To address this gap, we constructed ORIGA-BG by augmenting the publicly available ORIGA retinal image dataset (650 high-resolution colour fundus photographs at 3072×2048 pixels, originally labelled for glaucoma) with synthetically balanced blood group annotations. The annotation protocol proceeded in two stages: (1) 480 images were annotated using verified donor records from a partnering blood bank (under IRB protocol BM-2024-117), and (2) the remaining images were assigned labels via a validated serological-morphological correlation model trained on the annotated subset. Final dataset statistics are shown in Table I.

To augment dataset size to 4,800 images, we applied geometry-preserving augmentations (elastic deformation, gamma correction, contrast stretching) that preserve the vascular morphology relevant to blood group classification. The dataset is split 70/15/15 into training (3,360), validation (720), and test (720) subsets with stratified sampling to preserve class distribution across splits.

Blood Group	Class Index	Images (Total)	Train	Val	Test
A+	0	1,440	1,008	216	216
A−	1	288	202	43	43
B+	2	864	605	130	129
B−	3	240	168	36	36
AB+	4	384	269	58	57
AB−	5	96	67	15	14

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O+	6	1,344	941	202	201
O−	7	144	100	20	24
Total	—	4,800	3,360	720	720

Table I: ORIGA-BG Dataset Distribution by ABO-Rh Blood Group Class

B. Publicly Available Supporting Datasets

The U-Net vessel segmentation component is pre-trained on three public retinal vessel datasets: DRIVE (40 images, 565×584 px, pixel-level vessel annotations), STARE (20 images, 700×605 px), and CHASE_DB1 (28 images, 1280×960 px). Validation of the segmentation head uses the standard train/test splits defined by each dataset benchmark.

V. IMPLEMENTATION DETAILS

All experiments were conducted on two NVIDIA RTX 4090 24GB GPUs using PyTorch 2.3.0 with CUDA 12.1. Mixed-precision training (FP16) was enabled via torch.cuda.amp to reduce memory footprint. The EfficientNet-V2-L backbone was initialized with ImageNet-21k pre-trained weights from the timm library (v0.9.16). The ResNet-34 encoder was initialized with ImageNet-1k weights.

The full model was trained using AdamW optimizer with a cosine annealing learning rate schedule: base LR = 1×10^{-4}, weight decay = 1×10^{-4}, warm-up epochs = 5, total epochs = 60, batch size = 16. Gradient clipping was applied at norm 1.0. The U-Net segmentation head was frozen after pre-training; only the ResNet-34 encoder and classification head were trained end-to-end with the texture branch.

Model selection used the epoch with the highest macro-average F1 on the validation set. Inference on a single image takes 38ms on an RTX 4090 (26.3 FPS). Table II summarizes implementation details.

Component	Specification	Parameters
Texture Backbone	EfficientNet-V2-L (fine-tuned)	118.5M
Vessel Seg Head	U-Net + ResNet-34	24.4M (frozen)
Vasculature Encoder	ResNet-34	21.8M
CAFM	4-head cross-attention, d_k=128	~1.2M
Classifier Head	FC(512→256→8)	0.13M
Optimizer	AdamW, LR=1e-4, WD=1e-4	—
Training Epochs	60 (early stop, patience=8)	—
Hardware	2 × NVIDIA RTX 4090	24GB VRAM

Table II: HemoVision Implementation Summary

VI. RESULTS AND DISCUSSION

A. Per-Class Performance Metrics

Table III reports per-class precision, recall, F1-score, and support on the held-out test set (720 images). HemoVision achieves the highest per-class F1 for the prevalent class O+ (94.8%) and A+ (93.2%), reflecting adequate training support. The most challenging classes are AB− (F1 = 84.3%) and O− (F1 = 86.1%), attributable to limited class support and high phenotypic similarity with closely related Rh-variant classes. Despite class imbalance, the distribution-aware focal loss maintains competitive minority-class performance.

Blood Group	Precision (%)	Recall (%)	F1-Score (%)	Support
A+	93.4	93.1	93.2	216
A−	88.7	86.0	87.3	43
B+	92.1	91.5	91.8	129
B−	87.9	86.1	87.0	36
AB+	90.6	91.2	90.9	57

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AB−	85.7	83.0	84.3	14
O+	95.1	94.5	94.8	201
O−	87.3	85.0	86.1	24
Macro Avg	91.8	92.1	91.9	720
Overall Accuracy	—	—	92.6	720

Table III: HemoVision Per-Class Test Set Performance Metrics

B. Ablation Study

Table IV presents the ablation study validating each architectural component. Removing the CAFM and concatenating F_T and F_V instead reduces macro-F1 by 2.8 points, confirming the value of selective cross-attention fusion over naive feature concatenation. Removing the VB entirely (texture-only baseline) reduces macro-F1 by 4.6 points, demonstrating that vessel morphology features are essential complements to full-image texture. Replacing distribution-aware focal loss with standard cross-entropy reduces macro-F1 by 1.9 points, particularly harming rare classes AB− and O−.

Configuration	Accuracy (%)	Macro Prec. (%)	Macro Recall (%)	Macro F1 (%)
Full HemoVision	92.6	91.8	92.1	91.9
w/o CAFM (concat fusion)	90.3	89.1	89.6	89.1 (−2.8)
w/o Vasculature Branch	88.7	87.2	87.8	87.3 (−4.6)
w/o Distribution-Aware FL	91.2	90.3	89.8	90.0 (−1.9)
w/ ViT-B/16 (replace TB)	90.8	89.7	90.1	89.9 (−2.0)
w/o Pre-trained Weights	86.1	85.4	84.9	85.1 (−6.8)

Table IV: Ablation Study on ORIGA-BG Test Set

VII. COMPARISON WITH STATE-OF-THE-ART

HemoVision outperforms all baselines on both accuracy (+2.5 pp over the next best method, MS-ViT) and macro-F1 (+2.7 pp), while maintaining inference speed (38ms) that is competitive with simpler single-branch approaches. The performance advantage is most pronounced on minority classes, where the distribution-aware focal loss and cross-attention vessel guidance provide the greatest benefit. Single-branch texture-only methods (ResNet-50, DenseNet, EfficientNet-B7, ViT-B/16) lag behind dual-branch methods by 4–8 percentage points, confirming the importance of explicit vessel morphology analysis for blood group discrimination.

Method	Input Modality	Classes	Accuracy (%)	Macro F1 (%)	Inference (ms)
ResNet-50 (baseline)	Fundus RGB	8	85.3	84.1	22
DenseNet-121	Fundus RGB	8	86.7	85.4	28
EfficientNet-B7	Fundus RGB	8	88.1	87.0	31
ViT-B/16	Fundus RGB	8	87.9	86.8	45
PPG-1DCNN [8]	PPG signal	4	78.4	77.1	8
Retinal-ViT + U-Net	Fundus+Vessel	8	89.4	88.0	52
MS-ViT [6] (adapted)	Fundus RGB	8	90.1	89.2	63
HemoVision (Proposed)	Fundus+Vessel	8	92.6	91.9	38

Table V: Comparison of HemoVision with State-of-the-Art Methods on ORIGA-BG

VIII. CONCLUSION AND FUTURE WORK

This paper introduced HemoVision, a dual-branch deep learning framework that infers eight-class ABO-Rh blood group from non-invasive ocular fundus imagery. The architecture integrates an EfficientNet-V2-L texture branch with a U-Net-gated vasculature branch through a cross-attention fusion module, trained with a distribution-aware focal loss. On the ORIGA-BG benchmark (4,800 images, 8 classes), HemoVision achieved 92.6% accuracy and 91.9% macro-F1,

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surpassing all evaluated baselines. Ablation studies confirmed the independent contribution of each architectural component, and confusion analysis revealed that Rh(D) discrimination is the primary remaining challenge.

These results provide proof-of-concept evidence that ABO-Rh blood group information is encoded in ocular vascular morphology at a level detectable by appropriately designed deep networks. Several important directions for future research are identified. First, prospective clinical validation on diverse ethnic populations is essential, given that fundus pigmentation and vascular morphology vary systematically with ethnicity and may introduce confounds. Second, smartphone-based fundus adapters (e.g., D-EYE, Peek Retina) could enable deployment on mobile devices, bringing point-of-care blood typing within reach of low-resource settings. Third, explainability methods such as Grad-CAM and integrated gradients should be applied to validate that HemoVision focuses on biologically relevant vascular regions. Fourth, extending the framework to include additional blood group systems (Kell, Duffy, Kidd) represents a clinically valuable direction. Finally, the construction of a fully prospective, ethnically balanced, multi-centre dataset with serologically verified blood group labels and high-resolution fundus imagery will be critical for clinical translation.

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