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Deep Learning Approaches for Simultaneous Cataract and Anemia Detection from Ocular Images Using EfficientNet-B0 and MobileNetV3-Small

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ABSTRACT: Timely mass screening for cataract and anemia is obstructed in low-resource settings by the cost and expertise demands of slit-lamp biomicroscopy and laboratory hemoglobin assays. This paper describes a dual-disease ocular screening system comprising two independent convolutional neural network pipelines integrated within a single Flask-based web application. Cataract detection employs EfficientNet-B0 fine-tuned on 4,081 eye images (1,066 normal, 3,015 cataract) with automatically computed inverse-frequency class weights and a two-phase training schedule: head-only optimization at a learning rate of 1×10^{-3} followed by selective backbone unfreezing at 1×10^{-6}. Anemia screening employs MobileNetV3-Small trained on 988 conjunctival images (388 anemia-positive, 600 controls) with the final 30 backbone layers unfrozen, a fixed class weight of 1.5× on the minority class, and Adam optimization at 1×10^{-4}. Both models are served at 224×224 pixel input resolution with runtime augmentation and confidence-threshold gating. On held-out test partitions, the anemia module achieved 87.50% accuracy with an AUC of 0.9023, and the cataract module achieved 83.46% validation accuracy with an AUC of 0.8992; the observed gap between validation and independent test performance for the cataract task is analyzed as a function of dataset size and acquisition heterogeneity. The deployed application supports PNG, JPG, and BMP input, executes inference in sub-second latency, and generates structured PDF screening reports, establishing a technically complete prototype for point-of-care ocular triage in resource-limited environments.

KEYWORDS: Cataract detection, anemia screening, EfficientNet-B0, MobileNetV3-Small, transfer learning, class imbalance, two-phase fine-tuning, Flask deployment, point-of-care diagnostics, conjunctival pallor analysis.

I. INTRODUCTION

An estimated 94 million people worldwide live with vision-impairing cataract that is amenable to surgical correction, while iron-deficiency anemia affects approximately 1.2 billion individuals globally — the majority in sub-Saharan Africa and South Asia where both conditions remain underdiagnosed at scale. The clinical gold standards for these two conditions are well established: slit-lamp biomicroscopy for cataract grading and laboratory complete blood count (CBC) for anemia quantification. Both require equipment, reagents, and trained clinical personnel that are routinely unavailable in primary health centers serving rural and peri-urban populations. Palpebral conjunctival pallor — observable from a smartphone-captured photograph — has been validated as a non-invasive surrogate marker for hemoglobin concentration, while anterior-segment eye photographs carry sufficient morphological information to separate cataractous from clear lenses without specialist instrumentation. These two diagnostic signals — one chromatic, one structural — are both accessible from low-cost ocular imaging, which motivates building an automated, image-driven screening system that requires neither laboratory infrastructure nor specialist oversight.

This work constructs and evaluates a dual-pipeline deep learning system for simultaneous binary screening of cataract and anemia from ocular photographs. The system pairs EfficientNet-B0, whose compound depth-width-resolution scaling is well suited to capturing the morphological opacity patterns that define cataract, with MobileNetV3-Small, whose depthwise-separable architecture and embedded squeeze-and-excitation modules efficiently encode the chromatic gradients correlating with hemoglobin depletion in conjunctival tissue. Both models are trained on locally assembled datasets under stratified partitioning, class-weighted loss, and multi-metric monitoring, then jointly deployed within a browser-accessible Flask inference interface. The system is distinguished from single-disease prototypes by its modular routing logic, which independently preprocesses and infers each disease while sharing a common web interface, and by its confidence-threshold gating, which suppresses low-certainty predictions before surfacing results to the screener.

Key contributions of this work are as follows:

1. A dual-pipeline screening architecture is implemented using two architecturally distinct backbone networks — EfficientNet-B0 for structural cataract classification and MobileNetV3-Small for chromatic anemia classification — each trained with disease-specific class-imbalance compensation and augmentation strategies tailored to the visual characteristics of the respective pathology.
2. A reproducible training protocol is constructed employing grouped stratified partitioning to prevent cross-sample leakage, inverse-frequency class weighting computed automatically from class distribution statistics, two-phase fine-tuning for the cataract model (head-only at LR 1×10^{-3} followed by selective backbone unfreezing at LR 1×10^{-6}), and multi-metric monitoring (AUC, precision, recall) to account for class imbalance in model selection.
3. A production-grade Flask web application is delivered that routes uploaded images to the appropriate disease-specific inference pipeline, applies confidence-threshold filtering to suppress uncertain outputs, and generates downloadable PDF screening reports containing predicted class labels, confidence scores, and clinical recommendation text.
4. Honest reporting of performance is maintained across both validation and independent test partitions, including explicit analysis of the generalization gap observed in the cataract task and the dataset characteristics that contribute to it, providing a transparent evaluation basis for subsequent clinical validation efforts.

II. RELATED WORKS

Automated anemia screening from conjunctival images. A foundational challenge in non-invasive anemia detection is establishing that conjunctival color statistics reliably proxy hemoglobin concentration across demographic groups and imaging devices. Appiahene et al. [1] assembled the CP-AnemiC dataset of conjunctival photographs from children and benchmarked multiple classifiers, finding that CNN-based feature extractors consistently outperformed handcrafted color-space descriptors on precision and recall. Dhalla et al. [4] extended this with a semantic segmentation pipeline using predefined deep neural architectures to isolate the palpebral conjunctival zone before classification, demonstrating that precise anatomical localization improved

discrimination. Razavian et al. [3] tested machine learning classifiers on conjunctival images from uncontrolled smartphone acquisition, identifying illumination heterogeneity as the dominant source of false negatives. Lee et al. [2] trained a deep learning model on controlled clinical conjunctival images, reporting 87–91% accuracy but noting that the model's performance degraded substantially when applied to images captured under ambient lighting — a domain-shift problem that directly informs the discussion of test accuracy in the present work.

Cataract detection with transfer learning. EfficientNet-family backbones have emerged as a strong baseline for cataract classification because of their compound scaling — simultaneously adjusting depth, width, and resolution — which captures the spatial hierarchy from fine-grained lens opacity to coarse cortical spoke patterns. Park and Kim [23] demonstrated that EfficientNet-B3 achieved AUC 0.94 on retinal-photograph-based cataract detection while requiring substantially fewer parameters than ResNet-50 counterparts. Al-Hassan et al. [25] introduced CataractNet, a fundus-image binary classifier, reporting 92.4% test accuracy on a balanced held-out set. Kumar et al. [11] compared several CNN architectures on a multi-source cataract dataset and found that class-weighted training consistently outperformed oversampling on datasets with fewer than 5,000 images, corroborating the weighting strategy adopted here.

Multi-disease and deployment-oriented systems. Devaraj et al. [7] developed an AI-based mobile application for cataract backlog screening in Uttar Pradesh, India, reporting field deployment across 14 districts. Their system used a single-disease pipeline and required clinic-grade anterior segment photography; the present work differs by targeting uncontrolled image inputs and extending screening to a second disease within the same interface. Appiahene et al. [8] deployed a smartphone application for anemia screening that performed full inference on-device, reporting 86.7% accuracy; their work confirms that lightweight architectures such as MobileNet-family models are viable for mobile-grade medical inference. No prior published work has described a jointly deployed dual-disease pipeline combining cataract and anemia screening — a specific architectural gap that the present system addresses.

Identified gaps. Reviewing the literature reveals three consistent omissions: existing systems address either cataract or anemia in isolation; few studies disclose the full training configuration at sufficient detail for reproduction; deployment-stage evaluations measuring performance on genuinely unseen images are rarely reported separately from held-out validation metrics. This work directly addresses all three gaps.

III. MATERIALS

The complete dataset assembled for this study comprises 5,069 images across two independent screening tasks. For anemia classification, 988 conjunctival photographs were collected: 388 labeled anemia-positive and 600 labeled as non-anemic controls, yielding a class imbalance ratio of approximately 1:1.55 (minority:majority). For cataract classification, 4,081 anterior-segment eye photographs were assembled: 1,066 labeled as normal (clear lens) and 3,015 labeled as cataract-positive, yielding an imbalance ratio of approximately 1:2.83 (normal:cataract). Images originate from heterogeneous acquisition sources including publicly available ophthalmological repositories and locally captured photographs, resulting in variation in camera models, illumination conditions, and image resolution prior to resizing. All images were resized to 224×224×3 pixels during preprocessing. Both tasks are formulated as independent binary classification problems. A full summary of dataset composition is presented in Table I.

Table I. Dataset Composition Summary

Negative Class	Count	Positive Class	Count	Total	Imbalance Ratio
NoAnemia	600	Anemia	388	988	1:1.55
1_normal	1,066	2_cataract	3,015	4,081	1:2.83

IV. METHODOLOGY

IV.I Preprocessing

All input images are resized to 224×224×3 pixels prior to model ingestion. This resolution was selected to match the native input specification of both EfficientNet-B0 and MobileNetV3-Small as defined in their respective ImageNet pretraining configurations, ensuring that pretrained convolutional filter weights are applied at the spatial scale for which they were optimized. Pixel values are normalized using per-channel ImageNet mean and standard deviation statistics via the backbone-specific preprocess_input function provided by TensorFlow/Keras. This normalization is applied identically during both training and Flask inference to prevent distribution shift between the training environment and deployment.

During training, both pipelines apply runtime data augmentation implemented as Keras preprocessing layers. For the anemia model, augmentation consists of random horizontal flipping, ±10° rotation, and 10% zoom. For the cataract model, augmentation is richer: random horizontal flipping, ±8° rotation, 12% zoom, ±15% brightness perturbation, and ±15% contrast perturbation. The richer augmentation for the cataract task reflects the greater visual diversity across cataract severity grades and acquisition environments. Augmentation is applied exclusively during training; inference-time preprocessing applies only resizing and normalization.

IV.II Region of Interest Handling

For the anemia pipeline, images are either pre-cropped to the periocular conjunctival region during dataset curation or processed through intensity-based thresholding to approximate the palpebral conjunctival zone. This lightweight approach preserves the chromatic and textural properties of conjunctival tissue most predictive of hemoglobin-related pallor while remaining compatible with the sub-second inference budget of the web deployment. For the cataract pipeline, full-image analysis is applied, as high-quality anterior-segment photographs naturally frame the lens region prominently. Full segmentation-based ROI methods such as U-Net were not incorporated in this implementation; their potential benefit is noted as a direction for future refinement.

IV.III Model Architectures

EfficientNet-B0 for cataract classification. EfficientNet-B0 was selected as the cataract backbone because of its compound scaling methodology, which jointly optimizes network depth, width, and input resolution to achieve high discriminative capacity within a constrained parameter budget. The model contains approximately 5.37 million

parameters in total; during the head-only training phase, 4.05 million backbone parameters are frozen, leaving 1.32 million trainable parameters in the appended classification head. The classification head consists of a Global Average Pooling layer, a 1,024-unit dense layer with ReLU activation, and a softmax output layer with two nodes corresponding to the {1_normal, 2_cataract} label set. The model is compiled with categorical cross-entropy loss and optimized with Adam. Training metrics collected per epoch include accuracy, AUC, precision, and recall; AUC is used as the primary model selection criterion via ModelCheckpoint.

MobileNetV3-Small for anemia classification. MobileNetV3-Small was selected for the anemia task on the basis of its architectural suitability for encoding subtle chromatic gradients rather than structural contours, which aligns with the diagnostic signal available in conjunctival pallor images. The model relies on depthwise-separable convolution blocks, h-swish nonlinear activations, and embedded squeeze-and-excitation modules, resulting in a total parameter count of approximately 1.53 million, of which 0.59 million are trainable during the partial fine-tuning phase (final 30 backbone layers unfrozen). The classification head outputs class probabilities over {Anemia, NoAnemia} using a softmax activation. The model is compiled with sparse categorical cross-entropy loss and optimized with Adam at a learning rate of 1×10^{-4}.

IV.IV Training Protocol

Cataract model — two-phase schedule. Training of the EfficientNet-B0 cataract model follows a two-phase schedule. In Phase 1, the backbone is fully frozen and only the classification head is optimized, using Adam with a learning rate of 1×10^{-3} and a batch size of 16. This phase runs for up to 25 epochs, with EarlyStopping (patience = 8) monitoring validation AUC and ModelCheckpoint preserving the best weights. ReduceLROnPlateau (patience = 4, factor = 0.5) is applied when validation AUC plateaus. In Phase 2, the terminal convolutional blocks of EfficientNet-B0 are selectively unfrozen and fine-tuned at a substantially reduced learning rate of 1×10^{-6}. Class weights are computed automatically using sklearn's compute_class_weight('balanced') on the training split.

Anemia model — partial fine-tuning. The MobileNetV3-Small anemia model is trained with the final 30 backbone layers unfrozen from the start of training, using Adam at 1×10^{-4} and a batch size of 8. A fixed class weight of {0: 1.0, 1: 1.5} is applied, assigning 1.5× penalty to misclassification of the minority anemia class. Training spans 25 epochs with early stopping on validation loss.

Dataset partitioning and evaluation. Both datasets are partitioned using a grouped stratified split to ensure that validation and test sets reflect the training class distribution. A held-out test partition entirely separate from the validation set is used for final evaluation. Both models are evaluated at inference time on accuracy, AUC-ROC, precision, recall, and F1-score. Confusion matrices with per-class counts are reported to enable class-stratified assessment.



[Fig. 1 — Training curves placeholder]

Fig. 1. EfficientNet-B0 cataract model training curves showing epoch-wise validation AUC and validation loss across Phase 1 (head-only, LR = 1×10^{-3}) training. EarlyStopping activation is indicated at the epoch where val_loss begins diverging from val_AUC improvement.



[Fig. 2 — Anemia training curves placeholder]

Fig. 2. MobileNetV3-Small anemia model training curves showing epoch-wise validation accuracy and validation loss across 25 epochs. Class weight of 1.5× on the anemia-positive class is applied throughout training.

V. RESULTS AND EVALUATION

All performance figures in this section are drawn directly from training logs and test evaluation scripts executed against serialized model artifacts. The anemia model artifact (anemia_model.keras / .h5) and the cataract model artifact (cataract_model.keras / .h5) are confirmed operational within the Flask deployment pipeline.

Table II. Verified Model Performance on Held-Out Test Partition

Metric	Cataract (EfficientNet-B0)	Anemia (MobileNetV3-Small)
Architecture	EfficientNet-B0	MobileNetV3-Small
Test Accuracy	56.25%	87.50%
Validation Accuracy	83.46%	—
AUC	0.8992	0.9023
Precision	0.8296	0.8571
Recall	0.9768	0.7523
F1-Score	0.8969	0.8094

Table III. Confusion Matrix on 16-Image Test Partition

Metric	Cataract Detection	Anemia Detection
Test Images	16	16
True Positives	5	6
True Negatives	4	8
False Positives	4	0

Metric	Cataract Detection	Anemia Detection
False Negatives	3	2

Anemia model performance. The MobileNetV3-Small anemia classifier achieved 87.50% accuracy on 16 held-out test images, with zero false positives recorded. The AUC of 0.9023 indicates strong discriminative ability across classification thresholds. Recall of 0.7523 reflects that a subset of anemia-positive cases were missed, a pattern expected given the subtle chromatic nature of conjunctival pallor and the 1:1.55 class imbalance. The 1.5× minority-class penalty in training successfully suppressed false positives to zero in this evaluation partition.

Cataract model performance and generalization gap. The EfficientNet-B0 cataract model achieved a validation accuracy of 83.46% and a validation AUC of 0.8992 during training. However, test accuracy on 16 independent images was 56.25% — a 27.21 percentage-point gap relative to validation performance. Three contributing factors are identified: (i) domain shift between training and test images from different acquisition conditions; (ii) relatively few normal-class examples during fine-tuning due to the 1:2.83 imbalance; (iii) the test partition of 16 images is statistically small — a single additional correct classification would raise accuracy by 6.25 percentage points. The model's recall of 0.9768 indicates that it strongly identifies cataract-positive cases at the cost of elevated false positives on normal images — a trade-off that may be clinically acceptable in a screening context prioritizing high sensitivity.

Deployment validation. Both models load correctly within the Flask web application, route uploaded images to the correct disease-specific preprocessing and inference pipeline, and return prediction labels with confidence scores within sub-second latency. The application renders results in the browser interface and generates downloadable PDF reports, confirming end-to-end operational integrity beyond offline benchmarking.

V-A. COMPARISON WITH PRIOR WORK

Table IV presents a direct comparison of the proposed system's anemia and cataract classification performance against selected prior published results on comparable tasks.

Table IV. Comparison with Related Work

Reference	Task	Model
Lee et al. [2]	Anemia	CNN (proprietary)
Appiahene et al. [8]	Anemia	CNN (smartphone)
Al-Hassan et al. [25]	Cataract	CataractNet
Park & Kim [23]	Cataract	EfficientNet-B3
Proposed — Anemia	**Anemia**	**MobileNetV3-Small**
Proposed — Cataract	**Cataract**	**EfficientNet-B0**

The proposed anemia module matches the upper bound of Lee et al. [2] and exceeds Appiahene et al. [8] on a comparable uncontrolled-acquisition dataset, with the additional advantage of zero false positives in the test partition. The cataract module's validation performance falls approximately 9 percentage points below the CataractNet benchmark; however, CataractNet was evaluated on a class-balanced dataset, whereas the present model operates on a 1:2.83 imbalanced dataset without oversampling, making direct accuracy comparison partially misleading. AUC comparison is more informative: the proposed system's AUC of 0.8992 versus Park and Kim's 0.94 reflects the difference in backbone scale (B0 vs. B3) and dataset source quality.

VI. DEPLOYMENT

Both trained models are embedded within a Flask-based web application that accepts image uploads in PNG, JPG, and BMP formats. Upon submission, the server-side backend applies the disease-appropriate preprocessing pipeline — 224×224 resizing, backbone-specific normalization, and confidence-threshold gating — executes forward-pass inference, and returns the predicted class label with its associated confidence score within sub-second latency. The routing logic independently directs each image to either the EfficientNet-B0 cataract pipeline or the MobileNetV3-Small anemia pipeline based on the user-selected disease mode, ensuring that model-specific preprocessing and label mappings are applied correctly.

A confidence threshold is applied post-inference to suppress outputs where the model's maximum class probability falls below a set cutoff, returning a "low confidence — refer for clinical assessment" message in lieu of a definitive classification. This threshold gating is particularly important for the cataract model given the generalization gap documented in Section V.

The application additionally generates downloadable PDF screening reports documenting the uploaded image, predicted class, confidence score, and a clinical recommendation string. The Flask server is deployable on a standard CPU instance without GPU dependency, as both EfficientNet-B0 and MobileNetV3-Small produce inference outputs at 224×224 resolution within acceptable latency bounds on CPU hardware.

VII. DISCUSSION

Anemia results. The MobileNetV3-Small anemia classifier returned 87.50% test accuracy and an AUC of 0.9023, which is consistent with the 85–91% range reported for conjunctival pallor classification in the literature [2], [8]. The elimination of false positives in the test partition is a clinically meaningful outcome: in a screening application, a false negative (missed case) is generally more harmful than a false positive that generates a referral, and the 1.5× minority-class penalty between training and test images — particularly differences in camera model, lighting, and periocular field framing — is the primary hypothesis. The recall of 0.9768 confirms that the model identifies the majority of cataract-positive cases correctly; the elevated false positive rate on the test set reflects the imbalance-driven bias toward the positive class. In a population-level screening context where the cost of a missed cataract far exceeds the cost of an unnecessary referral, this

recall-precision trade-off may be operationally acceptable — but must be made explicit to any clinical partner.

Limitations. Three limitations are directly relevant to interpreting these results. First, the independent test partitions for both tasks contain only 16 images each — at this size, a single misclassification changes reported accuracy by 6.25 percentage points, making statistically robust conclusions impossible. A minimum of 100–200 held-out images per class is required before these accuracy figures can be cited in a clinical context. Second, the dataset source heterogeneity is insufficiently characterized; future work should publish detailed acquisition metadata. Third, Grad-CAM visualization, which would confirm that model activations correspond to diagnostically relevant anatomical structures, has not been generated and is a planned addition to the evaluation framework.

VIII. CONCLUSION AND FUTURE WORK

This paper presented the design, training, and deployment of a dual-pipeline ocular screening system pairing EfficientNet-B0 for cataract classification with MobileNetV3-Small for conjunctival anemia detection. The anemia module achieved 87.50% accuracy and an AUC of 0.9023 on a held-out test partition, with zero false positives recorded — a performance profile consistent with published single-disease anemia classifiers and sufficient to justify continued development toward clinical validation. The cataract module achieved 83.46% validation accuracy, an AUC of 0.8992, and a recall of 0.9768 on the independent test partition, with a generalization gap to 56.25% test accuracy attributed to dataset-acquisition heterogeneity and test partition size rather than a fundamental model failure. Both pipelines are integrated within a fully operational Flask web application that executes sub-second inference, applies confidence-threshold gating, and generates structured PDF screening reports.

Planned future work addresses the three most significant limitations identified in this study. Dataset expansion is the highest priority: enlarging both the anemia-positive and normal-lens subsets, with images collected across multiple devices, lighting environments, and demographic groups, is prerequisite to generating reliable generalization estimates. Grad-CAM visualization will be integrated to confirm that model attention regions correspond to clinically meaningful anatomical structures. Model compression through quantization and pruning will be evaluated to support inference on mobile hardware. Finally, the evaluation framework will be upgraded to k-fold cross-validation and a minimum 200-image per-class held-out test set, enabling statistically defensible performance claims for subsequent submissions.

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