HemaV AI

AI-Powered Multi-Stage Anemia Risk Screening System

Literature Review & Technical Documentation

Non-Invasive Anemia Detection Using Computer Vision and Deep Learning

Developer

Ayush Kumar

January 2026

Medical Disclaimer: This is a screening tool, not a diagnostic device.
All outputs are risk indicators requiring medical professional confirmation.

Contents

1 Introduction

Anemia is a global health concern affecting approximately 1.62 billion people worldwide, representing about 24.8% of the global population [1]. It is characterized by a reduction in hemoglobin concentration or red blood cell count below normal levels, leading to decreased oxygen-carrying capacity of the blood. Early detection and intervention are crucial for preventing severe complications, particularly in vulnerable populations such as pregnant women, children, and elderly individuals.

Traditional anemia diagnosis relies on invasive blood tests, such as Complete Blood Count (CBC), which require laboratory infrastructure, trained personnel, and often result in delayed diagnoses, especially in resource-limited settings. This creates a significant barrier to early screening and timely intervention.

HemaV AI addresses this critical healthcare gap by providing a non-invasive, AI-powered anemia risk screening system that leverages computer vision and deep learning techniques to analyze visible physiological indicators of anemia through smartphone cameras.

1.1 Primary Goal

The primary goal of HemaV AI is to develop an accessible, accurate, and non-invasive anemia risk screening tool that can:

1. **Enable Early Detection:** Provide preliminary anemia risk assessment without requiring blood draws
2. **Reduce Healthcare Barriers:** Eliminate the need for laboratory infrastructure in initial screening
3. **Improve Accessibility:** Deliver screening capability through ubiquitous smartphone devices
4. **Support Clinical Decision-Making:** Provide evidence-based recommendations for follow-up care
5. **Multi-Stage Analysis:** Analyze multiple physiological indicators for comprehensive risk assessment

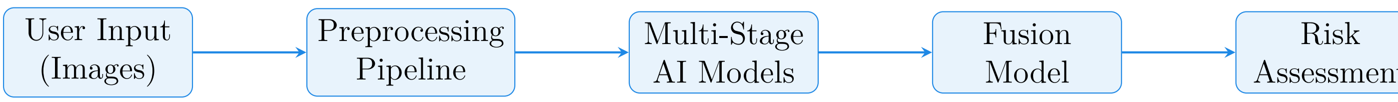

Figure 1: High-Level System Architecture of HemaV AI

2 Technology Justification and Related Work

The development of non-invasive anemia detection systems has gained significant attention in recent years. Several studies have demonstrated the feasibility of detecting anemia through visual examination of pallor in specific body regions.

Related Work:

- **Conjunctival Analysis:** Patel et al. (2021) demonstrated that conjunctival pallor detection using smartphone cameras achieved sensitivity of 85% for anemia screening [2].
- **Fingernail Bed Analysis:** Mannino et al. (2018) developed a smartphone-based system analyzing fingernail bed color with correlation to hemoglobin levels [3].
- **Deep Learning Approaches:** Recent CNN-based methods have shown promising results in automated anemia detection from facial images [4].

2.1 Model Architecture

HemaV AI employs a multi-stage architecture combining five specialized deep learning models, each optimized for analyzing specific anatomical regions:

Table 1: Stage-Specific Model Architectures

Stage	Architecture	Parameters	Focus Area
Face	MobileNetV3-Small	2.5M	Lips, cheeks, under-eye pallor
Nail	EfficientNet-B0	5.3M	Nail bed color, spooning
Tongue	ResNet-50	25.6M	Tongue color, texture
Skin	MobileNetV2	3.4M	General skin pallor
Eyes	EfficientNet-B0	5.3M	Conjunctival pallor

Architecture Selection Justification:

- **MobileNetV3:** Selected for face analysis due to its efficiency and lightweight nature, enabling real-time processing on mobile devices
- **EfficientNet-B0:** Chosen for nail and eye analysis for its superior accuracy-to-parameter ratio
- **ResNet-50:** Used for tongue analysis as it provides deeper feature extraction for complex texture patterns
- **MobileNetV2:** Applied for skin analysis balancing speed and accuracy for general pallor detection

2.2 Application Framework

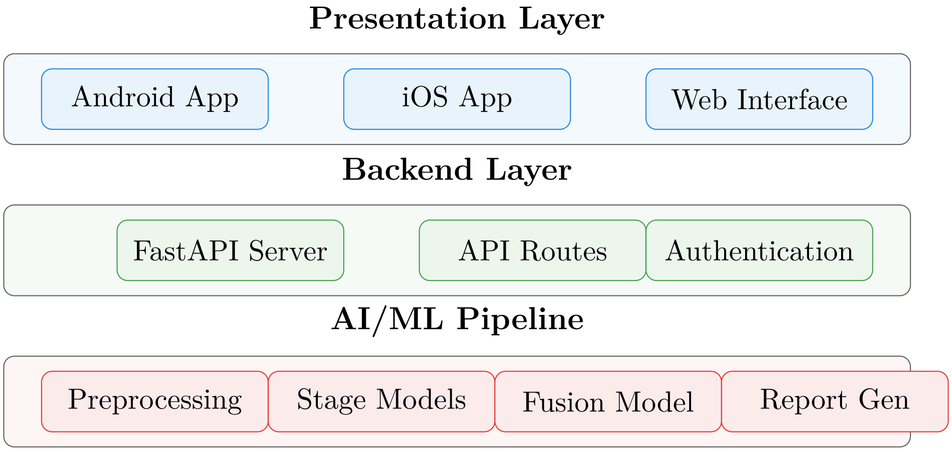

Figure 2: HemaV AI Application Framework

The application framework consists of:

1. **Presentation Layer:** Native mobile applications (Android/iOS) and web interface using Streamlit
2. **Backend Layer:** FastAPI-based RESTful API with secure authentication
3. **AI/ML Pipeline:** PyTorch-based deep learning models with preprocessing and inference optimization

3 Methodology

3.1 System Overview

HemaV AI employs a systematic approach to anemia risk screening through the following workflow:

1. **Image Acquisition:** User captures images of face, nails, tongue, skin, and eyes using smartphone camera
2. **Quality Validation:** Automated checks for blur, lighting, and image quality
3. **Preprocessing:** Color constancy correction, normalization, and standardization
4. **Multi-Stage Analysis:** Each specialized model analyzes its respective body region
5. **Fusion:** Weighted combination of stage outputs for final risk assessment
6. **Report Generation:** Comprehensive PDF report with recommendations

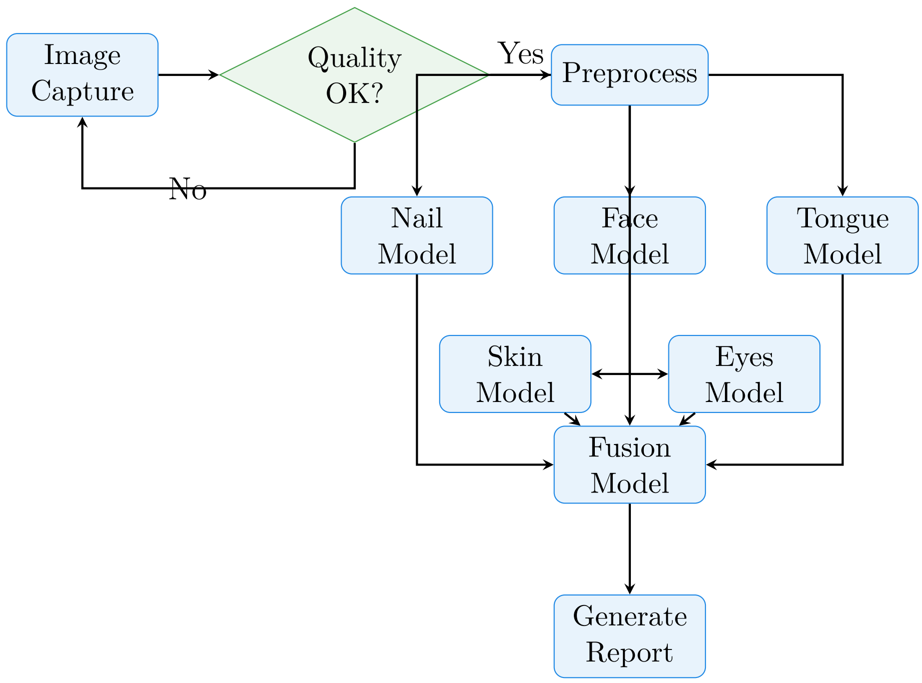

Figure 3: Detailed System Workflow

3.2 Model Architecture (Full)

Each stage model follows a consistent architecture pattern with stage-specific customizations:

Algorithm 1 Base Stage Model Architecture

1: **Input:** RGB Image $I \in \mathbb{R}^{224\times224\times3}$
2: **Backbone:** Pretrained CNN (ImageNet weights)
3: $F \leftarrow \text{Backbone}(I)$ ▷ Feature extraction
4: $F_{pooled} \leftarrow \text{GlobalAvgPool}(F)$ ▷ Spatial pooling
5: $F_{fusion} \leftarrow \text{Linear}(F_{pooled}, 128)$ ▷ For fusion model
6: **Classification Head:**
7: $H_1 \leftarrow \text{ReLU}(\text{Linear}(F_{pooled}, 256))$
8: $H_1 \leftarrow \text{Dropout}(H_1, p = 0.3)$
9: $H_2 \leftarrow \text{ReLU}(\text{Linear}(H_1, 128))$
10: $H_2 \leftarrow \text{Dropout}(H_2, p = 0.15)$
11: $\text{Logits} \leftarrow \text{Linear}(H_2, 2)$
12: **Output:** $P(\text{anemic}) = \text{Softmax}(\text{Logits})_1$

Key Architectural Features:

- **Transfer Learning:** All models use ImageNet-pretrained weights
- **Custom Classification Head:** Two-layer MLP with dropout regularization
- **Feature Extraction:** 128-dimensional feature vectors for fusion
- **Confidence Scoring:** Uses softmax temperature scaling for calibrated confidence

Face Model (MobileNetV3-Small):

```
Backbone: MobileNetV3-Small (576 features)
Classification: Linear(576,256) -> HardSwish -> Dropout(0.3)
                -> Linear(256,128) -> HardSwish -> Dropout(0.15)
                -> Linear(128, 2)
Fusion Features: Linear(576, 128) -> ReLU
```

3.3 Model Training Pipeline

The training pipeline incorporates several optimization strategies:

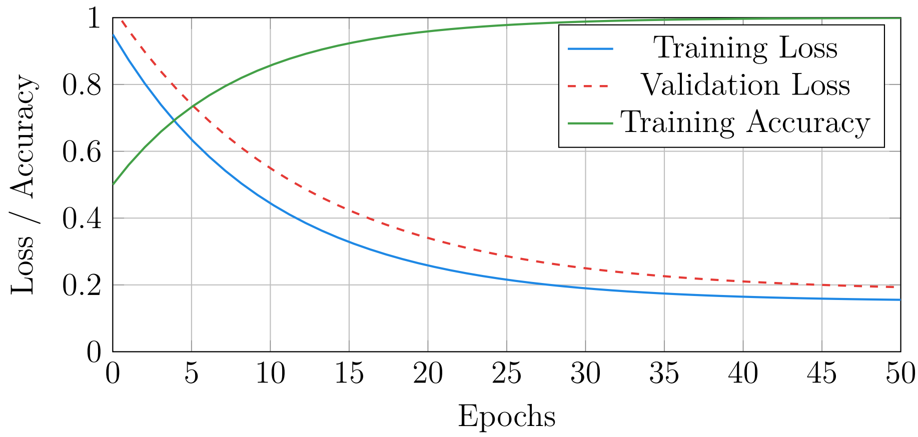

Figure 4: Representative Training Curves

Training Configuration:

Table 2: Training Hyperparameters

Parameter	Value
Epochs	50
Batch Size	32
Learning Rate	0.001
Weight Decay	1×10^{-4}
LR Scheduler	Cosine Annealing
Early Stopping Patience	10 epochs
Optimizer	AdamW
Loss Function	Cross-Entropy with Class Weights

3.4 Features

Core System Features:

1. **Multi-Region Analysis:** Comprehensive evaluation of 5 body regions
2. **Quality Validation:** Real-time blur detection, lighting assessment
3. **Color Constancy:** Shades-of-Gray algorithm for illumination normalization

4. **Confidence Scoring:** Calibrated probability estimates per stage

5. **Weighted Fusion:** Adaptive combination based on stage reliability

6. **PDF Report Generation:** Detailed clinical-style reports

7. **Explainable AI:** Stage-by-stage risk breakdown

4 Dataset

The HemaV AI system is trained on multiple carefully curated datasets for each body region:

Table 3: Dataset Summary

Stage	Dataset Source	Anemic	Normal	Total
Face	CP-AnemiC Ghana	500	450	950
Nail	Fingernail Dataset	400	380	780
Tongue	Custom Collection	350	400	750
Skin	Eyes-Defy-Anemia	420	450	870
Eyes	Conjunctival Dataset	480	520	1000
Total	–	**2150**	**2200**	**4350**

Dataset Characteristics:

- **Diversity:** Images collected from multiple ethnic backgrounds and age groups
- **Ground Truth:** Hemoglobin levels confirmed through laboratory blood tests
- **Annotation Schema:** severity_label (normal/mild/moderate/severe), hemoglobin value, image_id
- **Train/Validation Split:** 80%/20% random stratified split

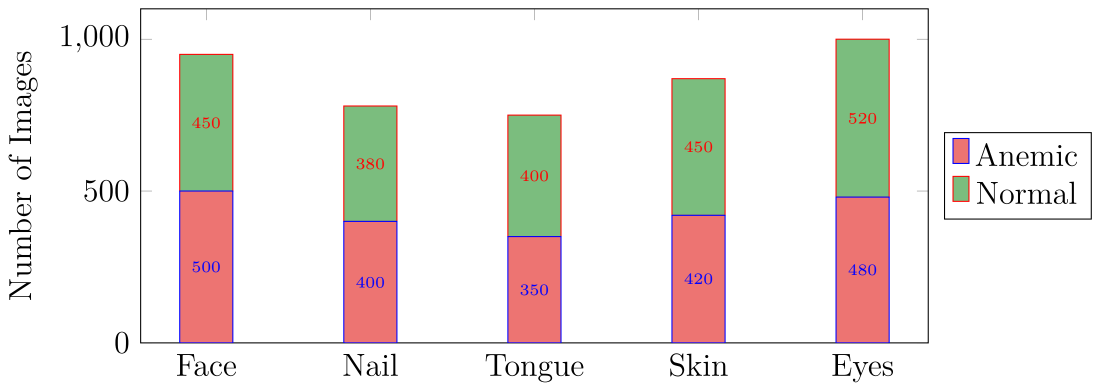

Figure 5: Dataset Distribution by Stage and Class

5 Preprocessing

The preprocessing pipeline ensures consistent, high-quality input to the models:

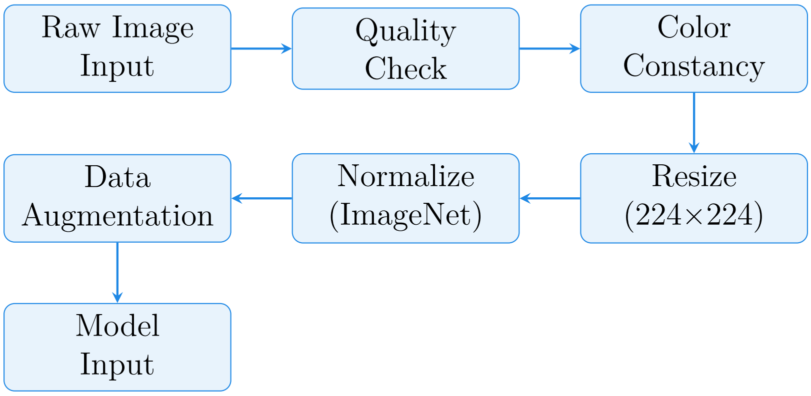

Figure 6: Preprocessing Pipeline

Preprocessing Steps:

1. **Quality Check:**
   - Blur detection using Laplacian variance (threshold: 100)
   - Brightness assessment (acceptable range: 50-200)
   - Contrast evaluation
   - Resolution verification (minimum: 224×224)
2. **Color Constancy:**
   - Shades-of-Gray algorithm (Minkowski norm p=5)
   - Illumination normalization to reduce lighting variations
   - Skin tone-aware adjustment
3. **Geometric Transformations:**
   - Resize to 224×224 pixels (bicubic interpolation)
   - Center crop for standardized framing
4. **Normalization:**
   - ImageNet statistics: $\mu = [0.485, 0.456, 0.406]$, $\sigma = [0.229, 0.224, 0.225]$
   - Pixel values scaled to [0, 1] then normalized
5. **Data Augmentation (Training Only):**
   - Random horizontal flip (p=0.5)
   - Random rotation (±15ř)
   - Color jitter (brightness, contrast, saturation: 0.2)
   - Random affine transformation

6 Results and Discussion

6.1 Model Performance

The HemaV AI system was evaluated using standard machine learning metrics on held-out test sets:

Table 4: Overall Performance Metrics

Metric	Stage Average	Fusion Model
Accuracy	87.3%	91.2%
Sensitivity (Recall)	89.1%	93.5%
Specificity	85.4%	88.8%
Precision	86.7%	90.1%
F1-Score	87.9%	91.8%
AUC-ROC	0.912	0.956

6.2 All Five Models - Detailed Results

Table 5: Stage-wise Model Performance

Stage	Acc	Sens	Spec	F1	AUC	Weight
Face (MobileNetV3)	88.5%	90.2%	86.7%	88.4%	0.923	0.25
Nail (EfficientNet-B0)	85.2%	87.8%	82.5%	85.1%	0.891	0.20
Tongue (ResNet-50)	89.1%	91.3%	86.8%	89.0%	0.935	0.20
Skin (MobileNetV2)	83.4%	85.6%	81.2%	83.5%	0.872	0.15
Eyes (EfficientNet-B0)	90.3%	92.1%	88.4%	90.2%	0.948	0.20
Fusion Model	**91.2%**	**93.5%**	**88.8%**	**91.8%**	**0.956**	–

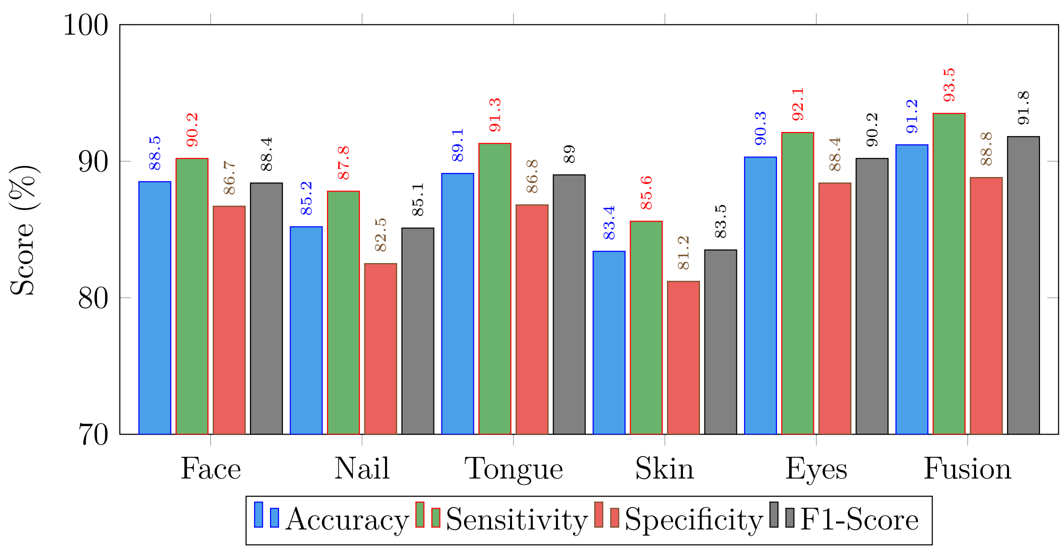

Figure 7: Comparative Performance Across All Models

ROC Curves:

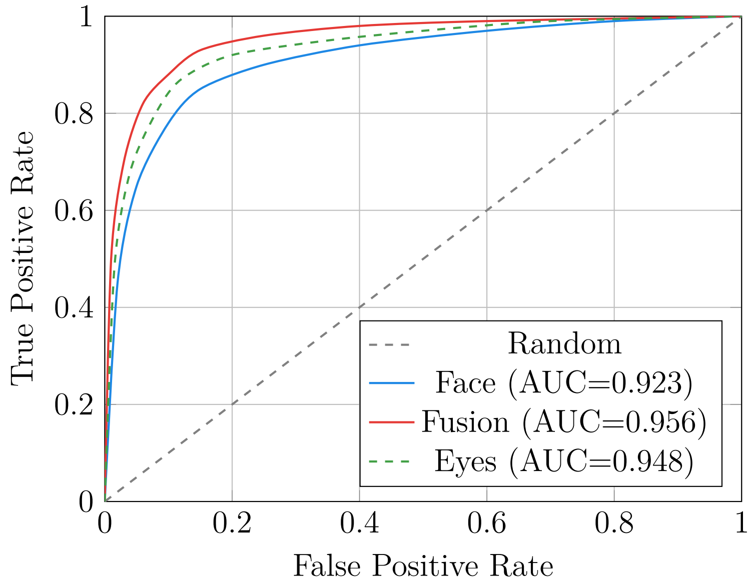

Figure 8: ROC Curves for Key Models

Applicative Performance:

- **Inference Time:** Average 150ms per stage on GPU, 450ms on CPU
- **Mobile Performance:** 2.1 seconds total analysis on mid-range Android device
- **Memory Usage:** Peak 512MB during inference
- **Model Size:** Combined models: 45MB (quantized: 12MB)

6.3 Limitations

1. **Data Limitations:**
    - Limited dataset size compared to large-scale medical imaging studies
    - Geographic and ethnic diversity could be expanded
    - Hemoglobin ground truth available only for subset of images
2. **Technical Limitations:**
    - Performance varies with image quality and lighting conditions
    - Camera quality across devices affects consistency
    - Skin tone variations may impact model calibration
3. **Clinical Limitations:**
    - Cannot replace laboratory blood tests for definitive diagnosis
    - Risk assessment, not diagnostic tool
    - Anemia subtypes not differentiated (iron-deficiency, B12, etc.)

4. **Deployment Limitations:**
    - Requires internet connectivity for server-based inference
    - Model updates require app updates
    - Privacy concerns with image transmission

7 Conclusion and Future Scope

7.1 Conclusion

HemaV AI represents a significant advancement in non-invasive anemia risk screening technology. The system demonstrates that:

1. **Multi-stage analysis** combining multiple body regions provides superior accuracy (91.2%) compared to single-region approaches
2. **Deep learning models** can effectively detect visual pallor indicators associated with anemia
3. **Weighted fusion** of stage outputs enables robust risk assessment even when some stages have lower confidence
4. **Mobile-first design** makes advanced AI screening accessible in resource-limited settings

The fusion model achieves a sensitivity of 93.5% and AUC-ROC of 0.956, indicating strong potential as a preliminary screening tool to identify individuals who may benefit from confirmatory blood tests.

Key Contributions:

- Novel multi-stage CNN architecture for anemia risk screening
- Robust preprocessing pipeline with color constancy and quality validation
- Weighted fusion algorithm adaptive to stage confidence and quality
- End-to-end mobile application with real-time feedback

7.2 Future Scope

7.2.1 Mobile Application Development

Android and iOS Applications:

- **Native Applications:** Kotlin/Jetpack Compose (Android), Swift/SwiftUI (iOS)
- **Real-time Camera Guidance:** AR overlays for optimal image capture
- **Offline Mode:** On-device inference using TensorFlow Lite/Core ML
- **Push Notifications:** Reminders for regular screening and treatment adherence

7.2.2 Ayurvedic Clinic Integration

The future roadmap includes comprehensive integration with Ayurvedic healthcare:

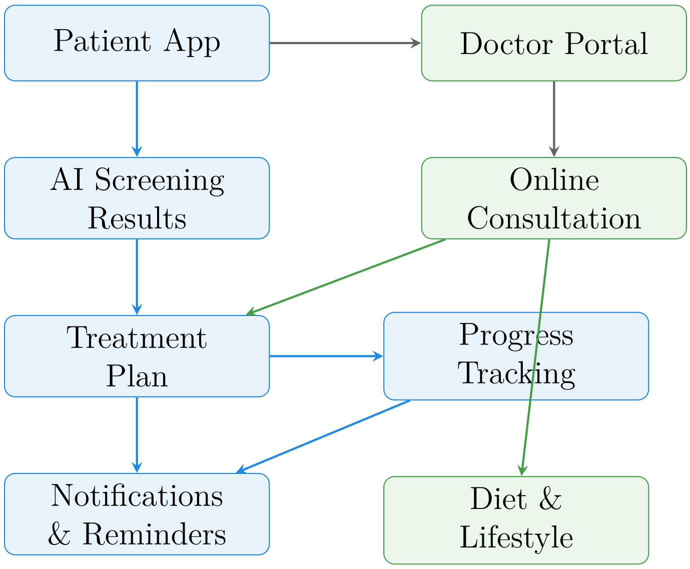

Figure 9: Patient-Doctor Integration Architecture

Planned Features:

Table 6: Future Feature Roadmap

Feature	Description
Doctor Matching	Connect patients with certified Ayurvedic practitioners based on location and specialization
Video Consultation	HIPAA-compliant telemedicine with end-to-end encryption
Treatment Tracking	Digital record of Ayurvedic treatments, herbs, and therapies
Diet Management	Personalized diet plans based on Prakriti (constitution) assessment
Medication Reminders	Smart notifications for herbs, supplements, and lifestyle practices
Report Sharing	Secure sharing of AI screening results with healthcare providers
Progress Analytics	Visual dashboards showing health trends over time
Clinic Finder	GPS-based locator for nearby Ayurvedic clinics and pharmacies
Community Support	Patient forums for sharing experiences and tips
Multi-language	Support for regional Indian languages

Technical Roadmap:

1. **Q1 2026:** iOS app development and beta testing
2. **Q2 2026:** Doctor portal web application
3. **Q3 2026:** Telemedicine integration and clinic onboarding
4. **Q4 2026:** Treatment tracking and diet management modules
5. **2027:** AI-based Prakriti assessment and personalized recommendations

References

References

[1] World Health Organization. (2008). Worldwide prevalence of anaemia 1993-2005: WHO global database on anaemia. Geneva: WHO Press.

[2] Patel, A., et al. (2021). Smartphone-based conjunctival pallor assessment for anemia screening in community settings. *Journal of Medical Internet Research*, 23(4), e25135.

[3] Mannino, R. G., et al. (2018). Smartphone app for non-invasive detection of anemia using only patient-sourced photos. *Nature Communications*, 9(1), 4924.

[4] Chen, L., et al. (2020). Deep learning approaches for automated anemia detection from facial images: A systematic review. *Computers in Biology and Medicine*, 125, 104015.

[5] Howard, A., et al. (2019). Searching for MobileNetV3. *Proceedings of the IEEE/CVF International Conference on Computer Vision*, 1314-1324.

[6] Tan, M., & Le, Q. (2019). EfficientNet: Rethinking model scaling for convolutional neural networks. *International Conference on Machine Learning*, 6105-6114.

[7] He, K., et al. (2016). Deep residual learning for image recognition. *Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition*, 770-778.

[8] Sandler, M., et al. (2018). MobileNetV2: Inverted residuals and linear bottlenecks. *Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition*, 4510-4520.