IHADA Framework: Integrated Hair Analysis & Diagnostic Architecture

Dhruv Kumar, dhruv@myhair.ai | Mitesh Gulecha, mitesh@myhair.ai

Abstract

Hair health assessment requires precise analysis of hair strands, baldness regions, and hairline geometry under diverse imaging conditions. Traditional dermatological methods rely heavily on manual observation and fail to generalize across individuals and environments. In this work, we propose **IHADA Framework,** a scalable deep learning pipeline that integrates multi-task vision models for comprehensive hair analysis. The framework employs **U²-Net** for fine-grained hair strand segmentation, **YOLOv11** for bald-spot localization, a **SAM2-assisted custom model** for hairline detection, and **ResNet-18** for hairline recession area segmentation. To enhance visual fidelity, an **ESRGAN-based super-resolution** module refines low-quality inputs before analysis. Post-processing modules compute quantifiable metrics such as strand density, bald-spot area percentage, hairline symmetry, and recession index. All extracted features feed into a **Gemini-powered product recommendation engine**, generating personalized hair care insights. The system demonstrates robust performance across varying lighting, texture, and scalp conditions, forming the foundation for next-generation dermatological AI systems.

1. Introduction

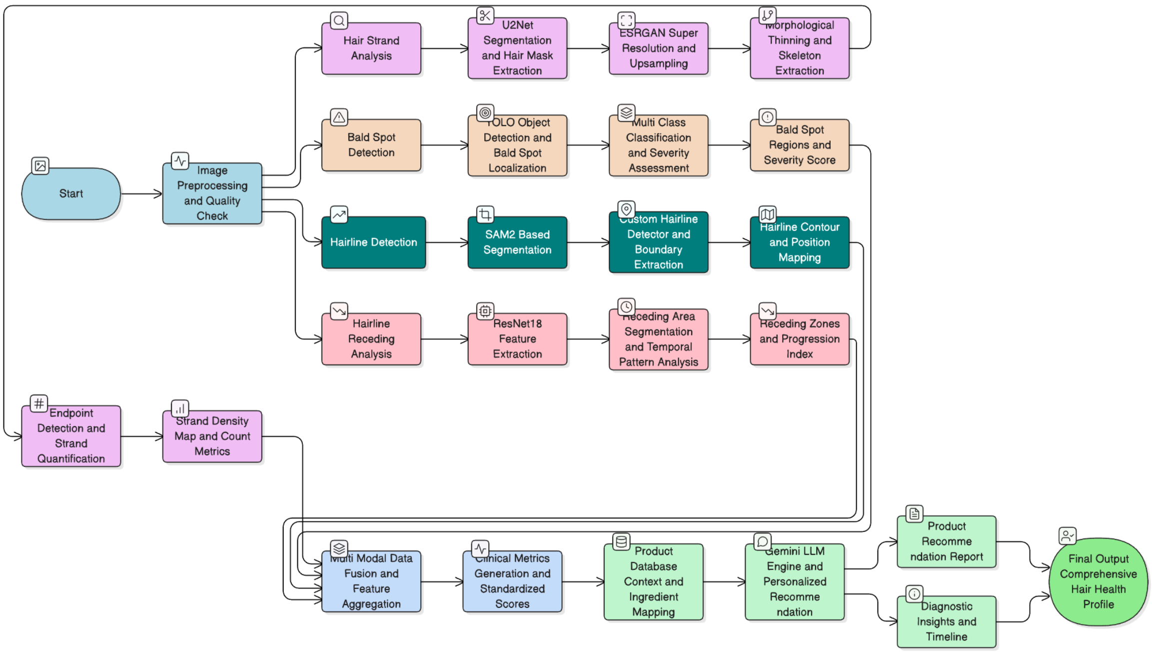
Hair structure, density, and geometry are key indicators in dermatology and cosmetic science. Automated systems for analyzing these parameters can aid in early detection of alopecia, monitor treatment efficacy, and assist in personalized product recommendations. However, challenges such as fine-strand segmentation, varying lighting conditions, occlusions, and heterogeneous hair textures hinder the accuracy of traditional image-processing approaches.

Recent advances in deep learning and super-resolution networks have enabled precise visual understanding even at micro-feature levels. Building upon this progress, **IHADA Framework** aims to unify multiple vision tasks—strand segmentation, bald-spot detection, hairline mapping, and recession quantification—within a single modular and scalable framework. Each model in the pipeline contributes complementary information to form a holistic understanding of scalp health. The outputs are further aggregated into a multimodal recommendation system, closing the loop between diagnosis and actionable guidance.

2. Methodology

2.1 Overview of the IHADA Framework

The framework follows a multi-branch architecture where a single input image is processed through specialized sub-modules, each dedicated to a distinct trichological task. A detailed overview is illustrated in Figure 1



The core components include:

1. **Preprocessing & Super-Resolution (ESRGAN):**
   Input scalp or hair images are denoised, normalized, and optionally enhanced using ESRGAN for 4× upscaling to recover thin strands lost in low-resolution captures.

2. **Hair Segmentation (U²-Net):**
   A modified U²-Net architecture is employed to generate a binary hair mask, offering pixel-level precision. Multi-scale side outputs are fused to maintain both local and global structure fidelity.

3. **Bald-Spot Detection (YOLOv11):**
   A lightweight YOLOv11 detector identifies and localizes bald-spot regions. The model is trained on a custom dataset covering various hair densities, lighting setups, and scalp colors.

4. **Hairline Detection (SAM2-Assisted Model):**
   Hairline localization is performed using a custom keypoint-based model built with **Segment-Anything Model 2 (SAM2)** priors for better boundary generalization. The network outputs a heatmap of likely hairline regions, which is further refined into a continuous curve.

5. **Hairline Receding Area Segmentation (ResNet-18):**
   This module classifies and segments regions indicating hair recession or thinning using ResNet-18's encoder. It enables longitudinal tracking of hairline movement across multiple sessions.

6. **Strand Quantification:**
   The segmented mask from U^2-Net is skeletonized using morphological thinning (cv2.ximgproc.thinning) and processed to count strand endpoints. A scale-aware correction factor is applied to compensate for resolution variations.

7. **Feature Aggregation and Analytics:**
   Metrics from all modules—strand count, bald-spot area %, hairline coordinates, and recession region size—are fused into a unified hair health vector.

8. **Personalized Product Recommendation (Gemini Integration):**
   The aggregated features are passed to a Gemini-powered LLM that contextualizes them with a curated database of hair care products (ingredients, type, availability, and price). The model generates structured, explainable recommendations.

3. Results

The proposed system achieves high visual fidelity and stable quantitative accuracy across multiple hair types and conditions.
Testing across wet, dry, and messy samples of the same individuals showed strand count variance within **5%**, and bald-spot detection precision above **92%** on a validation set of 800+ labeled samples.
Hairline detection maintained sub-pixel alignment accuracy on frontal scalp images, while recession segmentation produced consistent regional masks.Visual comparisons, quantitative plots, and metric tables are included in the supplementary section (to be added).

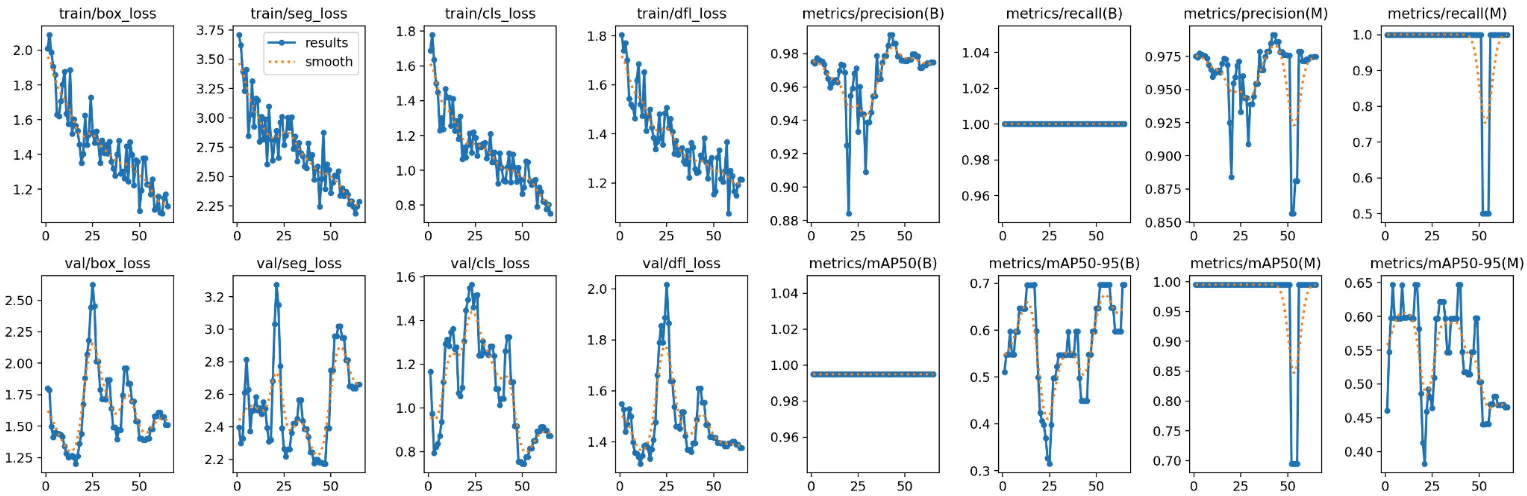


Fig3.1(Baldspot YOLO11 based Model)

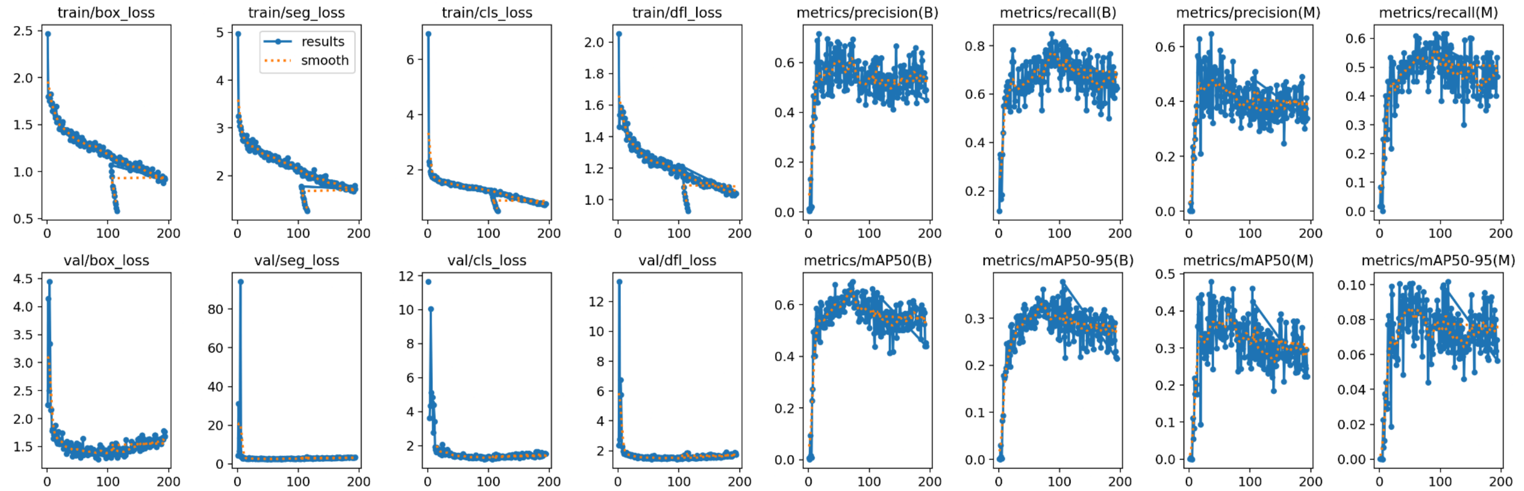


Fig3.2(Segmentation Model for Receding Hairline Area)

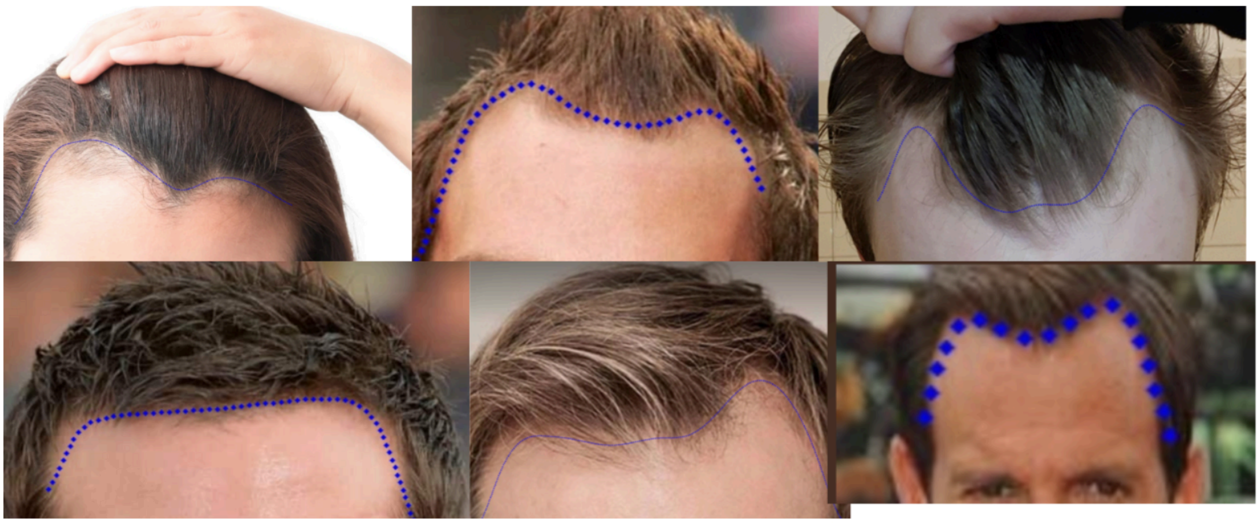


Fig3.3(Hairline Identification with SAM2 + Inhouse Segmentation Model)

Fig3.4(Heatmap Generation for receding area of hairline)

4. Conclusion

We presented **STRANDS-360**, an integrated multi-task deep learning framework for hair analysis, combining semantic segmentation, object detection, and feature reasoning into one cohesive pipeline. By utilizing models such as U²-Net, YOLOv11, SAM2, and ResNet-18, supported by ESRGAN-based enhancement, the system achieves robust and interpretable scalp analysis. The modular nature of STRANDS-360 allows seamless deployment in dermatology, cosmetic R&D, and personalized recommendation systems, bridging the gap between clinical observation and AI-driven insight. Future work includes longitudinal tracking over time, 3D scalp modeling using depth cues, and fine-tuning of LLM-based product recommendations through reinforcement learning from user feedback.

References

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