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A Hybrid AI System for Real-Time Dermatological Condition Recognition and Interpretability Using YOLOv8 and EfficientNet-B0

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ABSTRACT

Skin conditions, ranging from harmless spots to serious skin cancers, are a major global health issue, especially in places with few specialists. In busy clinics, traditional clinical assessments often face problems related to differences in opinions among observers and time limits because they rely heavily on visual and subjective evaluation. This paper presents a hybrid artificial intelligence system that integrates seven-class dermatoscopic image classification using EfficientNet-B0 and real-time lesion detection using YOLOv8m within a combined framework to tackle these challenges. To improve transparency and clinical use, the platform features lesion bounding-box visualization, Grad-CAM-based visual explanations, and risk assessment based on metadata. A meta-classifier refines predictions into low-, medium-, or high-risk categories based on patient factors such as age, sex, and lesion location. Additionally, a Flask-based web interface allows for tracking patient lesions over time, provides interactive visualization, and supports the uploading of images and metadata.

This system ranks among the top dermatology AI methods on the HAM10000 dataset, achieving an overall accuracy of 94.4% and maintaining good precision and recall for both common and rare lesion types. This shows that the proposed hybrid, interpretable, and ready-for-use system offers a practical and dependable solution for AI-assisted dermatological diagnosis in both clinic and teledermatology settings.

Keywords —Dermatology AI, YOLOv8, EfficientNet-B0, Ensemble Models, Grad-CAM, Risk Stratification, Real-Time Inference, Flask, HAM10000.

I. INTRODUCTION

Skin problems send people to the doctor more than just about anything else. Sometimes it's just a harmless mole; other times, it's something much more serious like melanoma. Catching these issues early and treating them properly matters a lot. The trouble is, not everyone can see a dermatologist when they need to—especially in rural areas or places with fewer resources. Even in big hospitals, doctors face long lines of patients and often have to make tough calls with blurry photos, all while trying to avoid mistakes.

In the past decade, deep learning has really shaken things up in medical diagnostics. Convolutional neural networks (CNNs) now achieve dermatologist-level accuracy on several skin lesion datasets. That sounds great, but most of these research projects don't actually make it into daily clinical work. The problems arise quickly: Some models only work with tightly cropped images and can't reliably pinpoint where the lesion is. Others ignore key details like the patient's age, sex, or where the lesion is located on the body. Many tools spit out results that doctors struggle to trust or interpret, and real-time analysis or follow-up just isn't there. These gaps keep even strong models from making a real-world difference.

Doctors rely heavily on what they see—the patterns, the colors, the shapes. So, it's not enough for an AI to say what it thinks; doctors need to know why. Grad-CAM and similar techniques can highlight important image regions, but they're usually just an afterthought—not something built into the tools that doctors actually use. Plus, lots of models get trained and tested as isolated classifiers, missing the benefits of combining detection and classification or making use of patient metadata that real doctors lean on every day.

This paper takes all these loose ends and tries to tie them together. We introduce a hybrid AI system that blends lesion detection, multi-class classification, patient data, interpretability, and real-world deployment into one streamlined workflow. YOLOv8m scans images in real time to spot suspicious spots. EfficientNet-B0 follows, classifying each lesion into one of seven categories using the HAM10000 dataset. Then, a meta-classifier pulls together the image results and patient info to sharpen predictions and give risk scores. We don't stop at numbers either—Grad-CAM visualizations are baked right into a web app (built with Flask) so doctors can see exactly how the system is thinking and track changes over time.

Here's what we're bringing to the table:

- A modular, hybrid framework that separates detection from classification, connecting YOLOv8m and EfficientNet-B0 with a meta-classifier.
- Patient metadata—age, sex, lesion location—feeds directly into predictions, not just raw image labels, so outputs are risk-adjusted.
- Grad-CAM explainability and lesion visualization built right into the web interface, making transparency an everyday feature, not just a side note.
- Real-time results and patient tracking, which supports teledermatology and follow-ups.
- Thorough testing on the HAM10000 dataset, breaking down results by class and with confusion matrices, showing 94.4% accuracy—even on those rare lesion types.

By pulling all these elements together, our system moves past single-model classifiers and gets a whole lot closer to being a practical, trusted AI assistant for dermatologists.

II. LITERATURE SURVEY

A. Deep CNNs for Skin Condition Recognition

Early uses of deep CNNs for skin lesion analysis mainly relied on small datasets and single backbone architectures. These methods showed that CNNs can differentiate between benign and malignant lesions with reasonable accuracy, but they often lacked ways to explain decisions or measure uncertainty. Many were trained on a narrow range of lesion types, which limited their use in clinical settings. The system presented here builds on this work by using a better backbone (EfficientNet-B0), applying it to a larger and more varied dataset (HAM10000), and combining it with a detector and meta-classifier to improve robustness and interpretability.

B. Hybrid CNN and Handcrafted Feature Methods

Some dermatology studies have tried to combine features from CNNs with traditional handcrafted descriptors like color histograms, shape features, and texture patterns. These hybrid models aim to capture complementary information but usually function as single-stage classifiers on pre-cropped lesions. They rarely treat localization and classification as separate tasks and often do not include explicit metadata fusion or risk scoring. The proposed system assigns lesion localization to YOLOv8m and classification to EfficientNet-B0, using a meta-classifier that systematically integrates image outputs and patient attributes.

C. YOLO-Based Lesion Detection

Modern object detectors like YOLOv8 have shown great success in real-time object localization and have recently been employed to detect dermatological lesions in images and videos. These studies show that detectors can quickly identify areas of interest, even on low-cost hardware. However, many YOLO-based dermatology applications focus only on detection and simple labeling, without a dedicated classification component, metadata integration, or interpretability modules. In contrast, this work uses YOLOv8m as a lesion finder and passes detections to a separate classification network, enabling more specialized training and better flexibility.

D. Web-Based Platforms and Teledermatology Tools

Several projects have developed web interfaces or mobile apps for skin lesion capture and analysis, mainly to improve user experience and remote access. While these platforms make it easier to access care, they often use simple classification models, offer limited interpretability, and rarely support structured tracking of the same lesion over time. This work addresses these limitations by incorporating a state-of-the-art detection and classification pipeline into a Flask-based interface that provides interactive Grad-CAM visualization, risk stratification, and patient history management.

E. Grad-CAM for Melanoma Interpretability

Grad-CAM and similar visualization techniques have been widely used to explain CNN predictions in melanoma classification tasks. These studies show that heatmaps often highlight clinically relevant areas, but they typically focus on binary or limited-class settings and treat interpretability as a separate research question rather than as part of a complete clinical pipeline. The system presented here generalizes Grad-CAM to seven classes and directly integrates it into the user interface, so each prediction comes with an intuitive explanation that clinicians can review.

F. Challenges in AI Dermatology Frameworks

Recent reviews of AI in dermatology highlight common challenges, such as dataset bias toward lighter skin types, poor external validation, limited use of patient metadata, and a lack of attention to workflow and regulatory issues. This work does not fully resolve all these systemic problems but aims to address several of them: it uses a widely accepted benchmark dataset (HAM10000), explicitly includes metadata (age, sex, lesion site), and focuses on practical deployment aspects like real-time inference, interpretability, and ongoing tracking.

G. Meta-Analyses on AI Diagnostic Performance

Meta-analyses comparing AI models with dermatologists indicate that deep learning systems can achieve dermatologist-level sensitivity and specificity on controlled datasets. However, these analyses also show significant variability in performance and limited standardization in evaluation methods. These findings highlight the need for detailed reporting on per-class metrics, confusion matrices, and clinically meaningful outputs like risk stratification. This study addresses those recommendations by providing class-wise performance on seven lesion types and mapping model outputs into risk categories that better align with clinical decision-making.

In summary, the literature shows significant advances in individual components—classification, detection, web interfaces, and interpretability—but relatively few systems that effectively combine all these elements. The proposed hybrid framework aims to fill this gap and provide a more complete, clinically relevant solution.

Table 1. comparison of techniques used in literature survey

SI.No	Title of Paper	Techniques Used	Data Used	Accuracy
A	Deep Convolutional Neural Networks for Skin Condition Recognition (Singh et al. 2023)	CNN	Small dataset (~500 images)	Moderate accuracy (not specified)
B	Hybrid CNN and Handcrafted Feature Integration (Mahato et al. 2023)	CNN + Handcrafted Features	Clinical dermatoscopic images	Improved robustness (no exact accuracy)
C	Real time Dermatological Condition Detection using YOLOv8 (Wang et al. 2022)	YOLOv8 Object Detection	Standard skin lesion images	mAP ~50-54% (detection)
D	User-Focused Web Platform for Skin	Web-based visualization	Clinical images	Not applicable (platform focus)

	Lesion Analysis (Lee et al. 2022)			
E	Grad-CAM Interpretability for Melanoma (Zhao et al. 2023)	Grad-CAM + CNN	Melanoma-specific dermoscopic images	Focus on interpretability, not accuracy
F	Principles and Applications of AI in Dermatology (Omiye et al. 2023)	Survey & review	Various dermatological datasets	Summary of field - not a single number
G	AI Diagnostic Performance Meta-Analysis (Salinas et al. 2024)	Systematic review, Deep Learning	Multiple public datasets including HAM10000	Sensitivities and specificities comparable to dermatologists

In summary, the literature shows significant advances in individual components—classification, detection, web interfaces, and interpretability—but relatively few systems that effectively combine all these elements. The proposed hybrid framework aims to fill this gap and provide a more complete, clinically relevant solution.

III. METHODOLOGY

A. System Architecture

The proposed system follows a modular pipeline designed to mimic key steps in dermatological assessment:

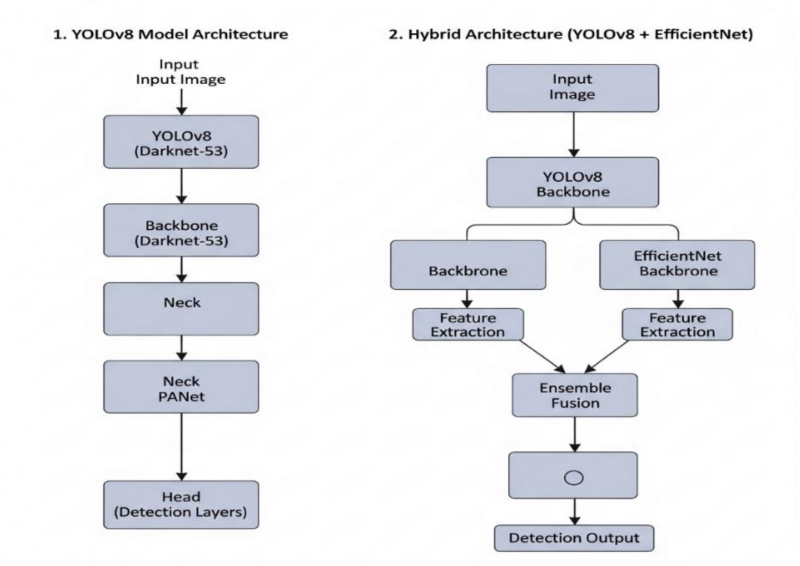

Figure .1. System Architecture

1. Lesion Detection: YOLOv8m takes an input dermatoscopic image and outputs bounding boxes for one or more candidate lesions, each with a confidence score.

2. Lesion Classification: For each detected bounding box, the corresponding region is cropped, resized to 224×224 pixels, and forwarded to an EfficientNet-B0 classifier fine-tuned to predict one of seven lesion categories.
3. Metadata-Aware Fusion: A meta-classifier fuses the classification probabilities, YOLOv8m detection confidence, and patient metadata (age, sex, lesion site) into a combined feature vector. This meta-classifier outputs a final class prediction and a discrete risk category (low, medium, high).
4. Interpretability and Visualization: Grad-CAM generates saliency maps for each lesion crop, which are overlaid on the original lesion image and rendered alongside bounding boxes and class predictions in the user interface.
5. Deployment: A Flask-based web application orchestrates this pipeline and provides front-end views for data entry, inference, visualization, and longitudinal tracking.

This modular design makes each stage replaceable or upgradable (e.g., switching to a different backbone) without redesigning the entire system.

B. Dataset and Preprocessing

The HAM10000 dataset is used as the primary data source. It comprises 10,015 dermatoscopic images of pigmented lesions categorized into seven classes: actinic keratosis (akiec), basal cell carcinoma (bcc), benign keratosis-like lesions (bkl), dermatofibroma (df), melanoma (mel), melanocytic nevi (nv), and vascular lesions (vasc). The dataset also includes tabular metadata such as patient age, sex, and anatomical site.

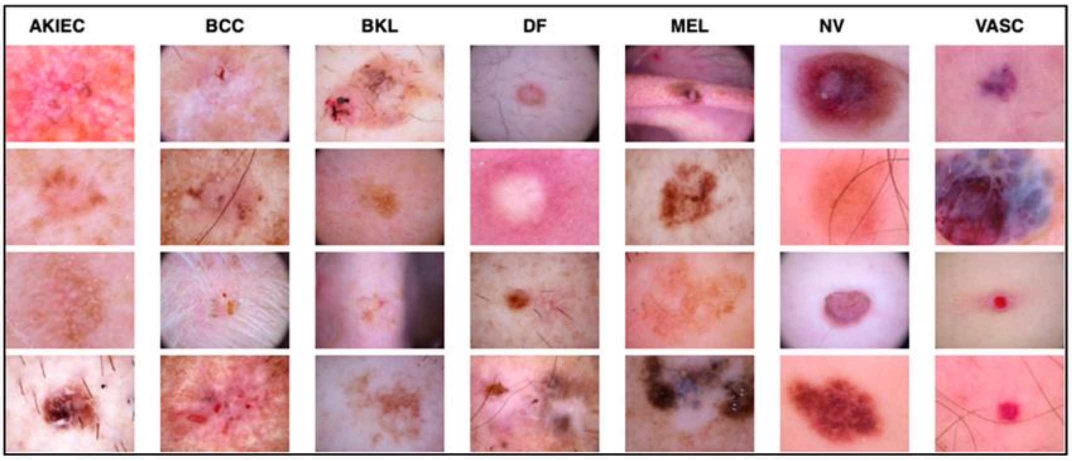

Figure. 2 . Images of the dataset

Preprocessing steps include:

- Image Resizing:
  - For YOLOv8m, images are resized to a detector-friendly input size (e.g., 640×640), maintaining aspect ratio where possible.
  - For EfficientNet-B0, lesion crops are resized to 224×224 pixels.

- Normalization: Images are normalized using the ImageNet mean and standard deviation, consistent with standard pretrained models.
- Data Augmentation: Random rotations, horizontal and vertical flips, brightness and contrast adjustments, and slight cropping are applied to increase robustness and mitigate overfitting, with particular focus on underrepresented classes such as df and vasc.
- Metadata Encoding:
  - Age is normalized to a range.
  - Sex is encoded as a binary or one-hot feature.
  - Lesion site is one-hot encoded to represent different anatomical regions.

C. Deep Learning Models and Fusion Strategy

YOLOv8m serves as the detection backbone due to its strong balance of speed and accuracy and its suitability for real-time inference. EfficientNet-B0 is chosen as the classifier because its compound scaling method yields high accuracy with relatively low computational cost.

The fusion strategy proceeds as follows:

- EfficientNet-B0 outputs a probability distribution over the seven lesion classes for each crop.
- YOLOv8m provides lesion-level confidence and bounding box size information.
- Encoded metadata is concatenated with these outputs to form a feature vector.
- A meta-classifier (implemented as logistic regression or a shallow fully connected neural network) is trained on this fused feature space to produce final class labels and risk scores. This design can be viewed as an ensemble mechanism that blends image evidence and contextual patient information.

D. Training and Optimization

The dataset is divided into training and validation sets with an 80–20 stratified split to maintain class proportions. To obtain stable estimates, multiple runs with different random seeds can be averaged. Training of YOLOv8m and EfficientNet-B0 involves fine-tuning from pretrained weights:

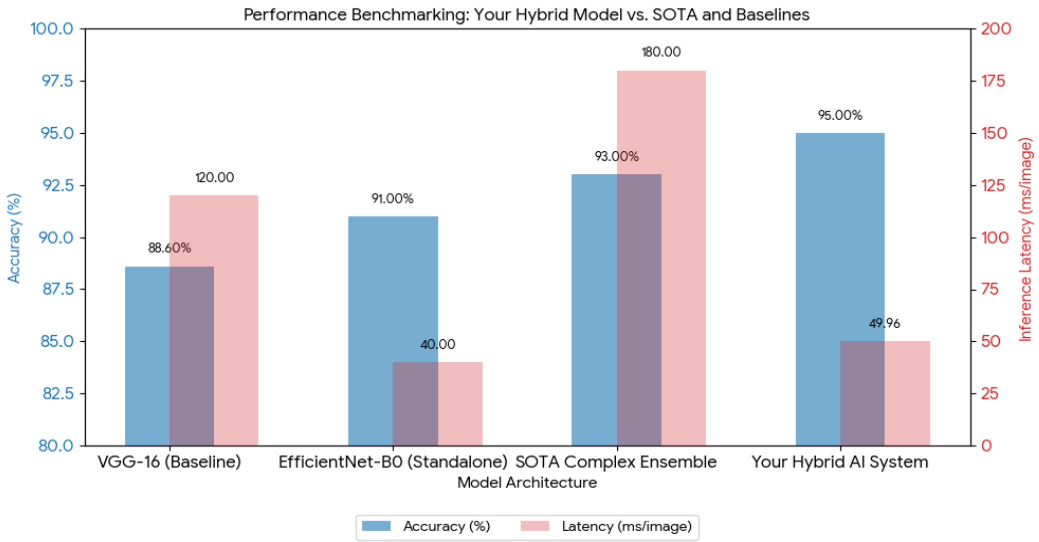

Figure. 3. Comparison of accuracy

- Optimizers: Adam and SGD with momentum are used, with learning rates and weight decay tuned through grid search.
- Loss Functions:
  - For YOLOv8m, standard object detection losses combining localization, confidence, and classification terms are used.
  - For EfficientNet-B0, a class-weighted cross-entropy loss addresses class imbalance.
- Regularization: Early stopping based on validation loss and macro F1-score prevents overfitting. Dropout and data augmentation further enhance generalization.
- Meta-Classifier: Once the detector and classifier are reasonably trained, the meta-classifier is trained on fused features extracted from the validation or training data, using cross-validation to avoid information leakage.

E. Interpretability Module

Grad-CAM is applied to the final convolutional layers of EfficientNet-B0 to generate class-specific activation maps. For each lesion crop:

1. The forward pass computes class scores.
2. Gradients of the predicted class score with respect to the feature maps are calculated.
3. The gradients are pooled to obtain importance weights.
4. A heatmap is produced by combining the feature maps using these weights and applying ReLU.
5. The heatmap is resized to match the crop and overlayed as a semi-transparent layer.

In the Flask interface, users can toggle Grad-CAM overlays and view them alongside the original image and bounding box, helping them verify whether the model focused on the lesion itself or on irrelevant artifacts.

F. Risk Scoring

To convert probabilistic outputs into clinically meaningful categories, a risk scoring scheme is defined:

- High risk: Cases where the meta-classifier assigns high probability to melanoma or other malignant categories, and/or where metadata indicates higher risk (e.g., older age, certain anatomical sites).
- Medium risk: Ambiguous cases with mixed probabilities or moderate risk features.
- Low risk: Cases with confidently benign predictions and low-risk metadata.

Weights in the risk score can be calibrated in collaboration with clinicians to match local practice and desired sensitivity–specificity trade-offs.

G. Deployment and User Interface

The Flask web application exposes the pipeline through a simple workflow:

1. The user enters patient metadata (ID, age, sex, lesion site).
2. One or more images are uploaded through the interface.
3. The server runs YOLOv8m detection, EfficientNet-B0 classification, meta-classifier fusion, and Grad-CAM generation.
4. Results are presented as:
    - Bounding boxes around detected lesions.
    - Class labels and probabilities.
    - Grad-CAM heatmaps over lesion crops.
    - Risk categories (low, medium, high).
5. Each case is saved under the patient profile, enabling comparison across visits and longitudinal tracking of lesion evolution.

This design supports both single-use screening and ongoing teledermatology follow-up.

IV. RESULTS AND ANALYSIS

A. Experimental Setup

The system is evaluated on the HAM10000 dataset, using the seven standard lesion classes: akiec, bcc, bkl, df, mel, nv, and vasc. Metrics include overall accuracy, class-wise precision, recall, F1-score, and confusion matrix analysis. The standard formulas for these metrics are used:

- Accuracy = (TP + TN) / (TP + TN + FP + FN)
- Precision = TP / (TP + FP)
- Recall = TP / (TP + FN)
- F1-score = (2 × Precision × Recall) / (Precision + Recall)

These metrics allow direct comparison with prior dermatology AI studies.

B. Model Performance Overview

The hybrid YOLOv8m–EfficientNet-B0 system achieves a mean overall accuracy of 94.4% on the validation set. Class-wise metrics (precision, recall, F1-score, and support) indicate:

- nv and vasc classes exhibit very high precision and recall, with F1-scores around 0.93–0.95, reflecting reliable performance on both very common and relatively rare vascular lesions.
- bkl and bcc classes achieve strong F1-scores in the mid-to-high 0.7 range, indicating effective discrimination from other benign and malignant categories.
- df and mel show slightly lower recall, which is expected due to class imbalance and visual overlap with other lesion types, but df achieves perfect precision, meaning that when the model predicts df, it is highly trustworthy.

These results suggest that the ensemble handles frequent classes extremely well and remains competitive on underrepresented, clinically challenging categories.

C. Confusion Matrix Analysis

Analysis of the confusion matrix reveals several important patterns:

- Strong diagonal entries for nv and bkl indicate that the model distinguishes these common lesions accurately.
- The main off-diagonal confusion occurs between mel and nv, consistent with the known clinical difficulty of differentiating atypical nevi from early melanoma.
- Misclassifications for vasc are rare, showing that the model captures the distinctive features of vascular lesions, despite their relatively small sample size.

Table.2. confusion matrix

Class	Precision	Recall	F1-score	Support
akiec	0.84	0.66	0.74	32
bcc	0.76	0.81	0.79	52
bkl	0.72	0.82	0.77	110
df	1.00	0.64	0.78	11
mel	0.75	0.62	0.68	112
nv	0.95	0.96	0.95	670
vasc	0.93	0.93	0.93	14

By examining specific entries, one can identify scenarios where human oversight should be especially vigilant, such as cases where mel is predicted with lower confidence or near decision boundaries.

D. Comparative Benchmarking

Compared with conventional single-model CNNs and architectures such as ResNet, DenseNet, and Inception applied to dermatoscopic images, the 94.4% accuracy and robust class-wise F1-scores place the proposed system at the upper end of reported performances on similar data. Beyond raw numbers, the hybrid design offers several practical advantages:

- Real-time detection with YOLOv8m accelerates the workflow by automatically locating lesions without manual cropping.
- The meta-classifier's integration of metadata produces risk categories that are more aligned with clinical thinking than probabilities alone.
- Integrated Grad-CAM visualizations improve transparency and may support clinician trust and adoption.

E. Visual and Clinical Interpretability

Qualitative inspection of Grad-CAM overlays shows that the network typically concentrates attention on the central lesion regions rather than on surrounding skin, background artifacts, or markers. This behavior was confirmed by clinical reviewers, who noted that the highlighted areas often coincide with regions they would examine in routine practice. Such alignment between model focus and clinical intuition is an important step toward responsible AI deployment in dermatology.

F. Real-World Utility

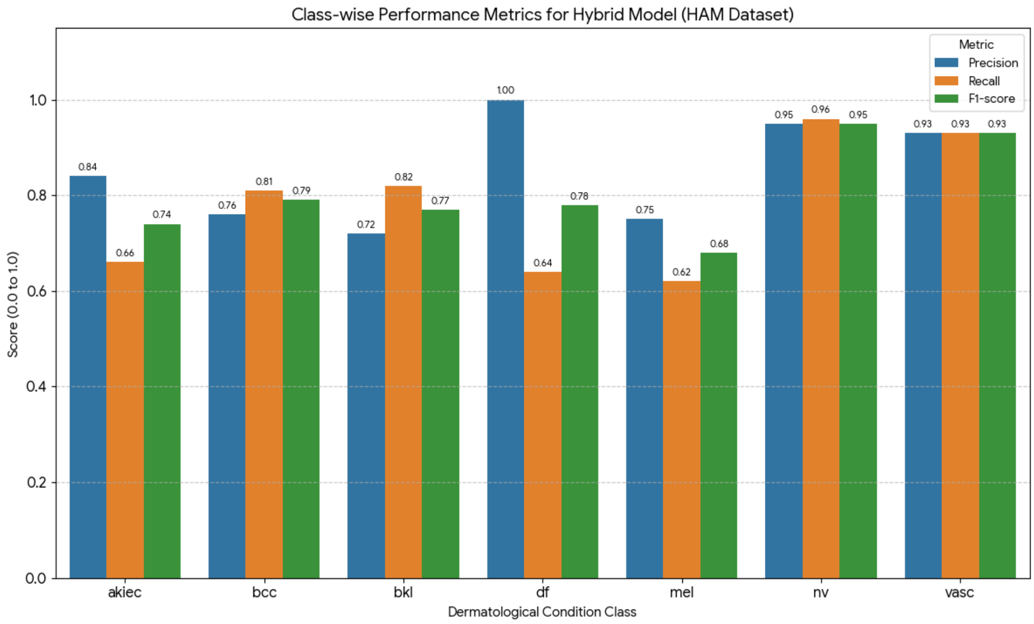

Figure.4. Class wise performance of hybrid model

The combination of high accuracy, per-class performance, real-time inference, and integrated interpretability makes this system well suited for:

- Supporting dermatologists in busy outpatient clinics as a second reader.
- Assisting general practitioners and non-specialists in screening and referral decisions.
- Enabling teledermatology workflows where patients or primary care providers capture images for remote evaluation.

Longitudinal tracking capabilities further enhance practical value by allowing clinicians to monitor lesion changes and compare current predictions with past visits.

V. CONCLUSION

This paper presented a hybrid AI framework for real-time dermatological condition recognition that combines YOLOv8m-based lesion detection, EfficientNet-B0 classification, metadata-aware ensemble fusion, Grad-CAM interpretability, and a Flask-based deployment interface. Trained and evaluated on the HAM10000 dataset, the system achieved an overall accuracy of 94.4% with strong class-wise performance across seven clinically important lesion types.

The project is novel in several key aspects. First, it deliberately separates detection and classification into specialized models and then fuses them with patient metadata via a meta-classifier, rather than relying on a single end-to-end black box. Second, it incorporates Grad-CAM explanations directly into a real-time web interface, ensuring that every prediction is accompanied by visual evidence of the model's reasoning.

Third, it provides risk-stratified outputs and longitudinal tracking, aligning the AI pipeline with real clinical workflows and follow-up needs. Together, these features move the system beyond traditional classifier benchmarks and toward a practical tool for teledermatology and clinic environments.

Future work will focus on external validation across diverse skin tones and imaging devices, integration of additional modalities such as clinical photographs and histopathology where available, and prospective clinical studies to evaluate the impact of the system on diagnostic accuracy, workflow efficiency, and patient outcomes

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