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Ethically Aware Dermatological AI

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Abstract: The rising rates of skin cancer across the globe have needed the development of largely automated webbing tools that can effectively identify skin cancer at early stages. These early findings play a prominent part in defining the outgrowth of cancer- stricken individualities. Although former attempts exercising traditional deep literacy algorithms have proven feasible in performing skin cancer groups directly enough, they've proven problematic in that they frequently operate as" black box" algorithmsthat constantlyfail in furnishing equal results across different races or skin textures. The current study proposes an advanced complex skin cancer opinion tool that can effectively classify skin cancer as either benign or cancerous with remarkable perfection while at the same time icing that it operates in an equal manner across all races and skin textures. The skin cancer opinion algorithm of choice has been grounded upon a complex model that synergizes the capabilities of Convolutional Neural Networks (CNN) alongside Vision Mills. substantially, EfficientNet- B0 has been employed effectively alongside Vision Mills because of its capabilities in effectively landing original textures alongside complex vascular features of skin lesions while at the same time effectively landing contextual features alongside structural harmony using Vision Mills. This research takes a preventive approach to the ethical use of AI and equitable access to algorithmic resources while treating users fairly. We also recognize that there is a bias towards lighter skin tones in medicaldatasets. The Individual Typology Angle (ITA) is used as a colorimetric measure of skin tone, which does not rely on human observers, thus eliminating subjectivity or inconsistency in labeling. We will also balance the representation of minorities within the Monk Skin Tone (MST) scale by utilizing StyleGAN to createaugments of existing data so we can create high-fidelity examples of different types of pathology on the MST scale. This will result in a robust, unbiased structure for the diagnostic framework when dealing with diverse populations around the world. Finally, to bridge the gap between computational output and physician trust in the results, the framework offers a multi - layered approach to explainability. The use of Grad-CAM visual heatmaps allows physicians to see the morphologic locations that influenced the model's decision and to verify the model's reasoning for diagnosis. Additionally, we can reduce the risk of errors resulting from the automated diagnosis by incorporating MC dropout techniques as measures of uncertainty, enabling the systems to assess their own confidence level

Keywords: Dermoscopy, Skin Cancer Classification, Individual Typology Angle (ITA), Latent Diffusion Models, Vision Transformers, Explainable AI (XAI), Artificial Intelligence (AI), Convolution Neural Network (CNN).

I. INTRODUCTION

Skin cancer and its most lethal type, melanoma, continue to pose a great threat to people's health all over the world. Early detection is the most important factor for survival, as the rate of death increases very quickly when the cancer is not caught at the early stage. Currently, the primary diagnostic method that is being used mostly is visual inspection (dermoscopy) done by doctors. This method is totally subjective, so it can easily lead to inter-observer variability where different experts might come to different conclusions, and non-specialists might find it hard to tell the cases apart. This subjectivity, plus the enormous number of cases, creates delays and bottlenecks in diagnosis. However, the present case is that the early screening process must be standardized and augmented. Thus, the researchers plan to have an Artificial Intelligence (AI) tool ready in the near future that would work as a 'second opinion' system - fast, objective, and very precise- which along with the reduction of cases of misdiagnosis (False Negatives) ultimately would result in the saving of lives, the standardization of the initial screening process, and the reducing of the heavy diagnostic burden on the health care systems.

1) Global burden and early detection significance: As skin cancer is caused by the unchecked growth of aberrant cells, it is a major public health concern. Basal Cell Carcinoma (BCC) and Squamous Cell Carcinoma (SCC) are non - malignant forms of skin cancer, while Malignant Melanoma is the more aggressive ty pe. Although melanoma has been linked to a higher death toll from skin cancer, the first type of NMSC makes up a larger portion of the two. The "gold standard for survival is early treatment, but the first symptoms of the disease often can easily be confused," according to the medical research that is currently available.
2) Challenges in manual dermoscopy: Dermoscopy has greatly increased the diagnostic power by allowing a magnified, lighted examination of the skin morphologies, with details such as the network, globules, and streaks, which are not visible to the human eye. However, the interpretation of dermatoscopic images is very experienced- dependent. A problem created by a similarity between types, described as "high intra -class variance, low inter-class similarity," makes it a challenging task. Additionally, the general lack of dermatologists worldwide, especially in remote areas, has created a bottleneck at the diagnostic step. Assist systems would therefore not be meant to replace a dermatologist but rather to be a "second opinion" tool.
3) Computer aided diagnostics (CAD): Past the ABCD rule, which stands for "Asymmetry, Border, Color, and Differential" characteristics, is one example of a computer-a "hand-crafted" feature in early CAD solutions. Despite being highly instructive, these solutions had a major flaw in that they ignored the range of lesion appearances in individuals with different skin tones under various lighting conditions. In the era of "Deep Learning" (DL), a paradigm shift occurred. Convolutional Neural Nets (CNNs), in contrast to traditional machine learning techniques, do not require feature "handcrafting." CNNs are able to identify intricate spatial hierarchies in images by using several nonlinear mappings in the network's hidden layers. These mappings range from edges in the earlier layers for straight forward images to intricate pathological distributions in the deeper ones.
4) Proposed Research and objectives: This work proposes to address several key challenges with respect to skin cancer detection automation through: (i) transitioning from traditional architectures to a high-throughput, Hybrid CNN-Transformer classifier pipeline, and (ii) significant expansion of the scope of the current studies focused on the HAM10000 dataset alone. The detailed technical objectives are thus set out as follows:

a) *Objective quantification of skin tone:* Use Individual Typology Angle to overcome subjective scales and ensure the model is tested on the full pigmentary spectrum, from Fitzpatrick I to VI.
b) *Data Balancing Equitably:* The over-inclusion of cases that are benign and lighter skin types is mitigated by the utilization of Latent Diffusion Models in synthesizing high-resolution melanoma samples conditioned on darker skin tones.
c) *Multi-Scale Feature Extraction:* Extract multi-scale features by using a hybrid backbone, which leverages both the local textural sensitivity of CNNs and the global spatial reasoning of Vision Transformers to capture minute follicular structures and overall lesion asymmetry.
d) *Clinical Interpretability and Reliability:* Integrating Grad-CAM for visual decision-mapping and Monte Carlo Dropout for uncertainty quantification, to ensure that the model acts like a transparent decision -support tool.This work aimed at demonstrating a bias-aware, yet computationally efficient model that retains high sensitivity for malignant lesions. The research provides a blueprint for equitable and explainable AI and thus will make deep learning methods adoptable in future accessible mHealth screening applications.

II. LITERATURE REVIEW

The previous decade witnessed a dramatic shift from traditional hand-crafted feature extraction to deep autonomous learning. The field has progressed through three distinct eras: Transfer Learning, Optimization & Ensembling , and the current era of Transformers and Explainability. By 2017, the primary goal was to create an automated, end -to-end skin cancer classifier. Because skin cancer is primarily diagnosed visually, they believed that Deep Learning specifically image recognition could provide high-quality screening to anyone with a smartphone, regardless of how close he or she might be to a clinic [1]. Then, in 2018, paradigms changed to dermoscopic imaging, that is, the magnification used by experts to see dermatoscopic images. This

current study named "Man against Machine" uses Inception v4 and has an even rigorous international comparison among 58 skin specialists of different levels of experience[2]. Schändl et al. took up the challenge of data scarcity in dermatological AI by publishing the open -source HAM10000 dataset, also referred to as "Human Against Machine." This dataset comprises 10,015 high -quality dermoscopic images that release the field from dependency on proprietary data [3]. In 2016, ResNet was introduced, which addresses the degradation problem in deep networks using identity shortcut connection s. This architecture allows the network to learn residual mappings rather than attempting to learn the direct underlying mapping [4]. By 2021, dermatologic AI research moved from the assessment of individual images to a patient-centric approach. The study correlated more than 33,000 images to data such as patient identifiers, age, sex, and body site, allowing algorithms to reproduce "ugly duckling sign"[5]. By uniformly balancing network depth, wid th, and resolution, Efficient Net presents Compound Scaling. Compared to conventional CNN architectures, this optimization is substantially smaller, faster, and more computationally efficient while achieving state-of-the-art accuracy [6]
In order to outperform Inception-V3 with higher parameter efficiency and speed, Xception introduced depth wise separable convolutions that handle spatial and channel-wise correlations independently[7]. By evaluating" resampling and cost- sensitive learning" strategies, Sauer and D'Alessandro (2020) demonstrate that reducing class imbalance is crucial to enhancing the sensitivity and dependability of automated melanoma detection[8]. By allowing neural networks to independently concentrate on the most discriminative local area s within a skin lesion, Li et al. (2020) created a "attention-guided framework" that increases diagnostic accuracy [9]. A "systematic review" of early CNN-based research is presented by Brinker et al. (2019), who conclude that deep learning models consiste ntly outperform dermatologists in experimental settings while pointing out the need for improved clinical validation [10]. As shown by Mahbod et al. (2021), fine-tuning multiple Efficient Net variants using transfer learning coupled with multi-scale image cropping significantly improves melanoma classification results, far better than the performance achieved in benchmark dermoscopic datasets using traditional CNN backbones [11]. In 2020 Gessert et al. employed ensembles of multi-resolution Efficient Nets combined with patient metadata, demonstrating that, when different image scales are combined with clinical data, the performance and robustness of skin lesion classification are significantly improved [12]. In (2017) Perez and Wang show that data augmentation methods, such as geometric transformations and color variations, contribute to significantly improving model generalization and reducing overfitting for deep learning tasks with limited datasets [13]. Later, in 2023, again contributed to developing sma rt system technology by presenting a hybrid model that combines IoT and AI for improved monitoring processes. This also highlights real-time data analytics, which plays a vital role in ensuring efficiency and overcoming potential challenges in the automation sector [14]

III. METHODOLOGY

A. Dataset Collection

The dataset considered for the analysis has been carefully compiled to address the vastly necessary need for quality and varied examples of dermoscopy images to be met. The first dataset compiled for the purpose of the study is derived from the International Skin Imaging Collaboration (ISIC) Archive. The two databases are a substantial lot consisting of dermoscopy images for malignant melanoma and melanocytic lesions, which have proven to be authentic after histopathological validation and/or follow-up, respectively. While these databases represent the 'gold standard' within lesion morphology, they have conventionally covered lighter skin types (Types I - III FIT provider's notes: This corresponds to Caucasians and people of Northern European descent.), wherea s we sought to fill the gap by using clinical skin dataset 17k, which is recognized to represent a sensible distribution for skin disorders for each Fitzpatrick skin scale among the six scales combined.

B. Data Preprocessing

Data preprocessing is the critical step to ensure model perform accurately. The dermoscopic images often exhibit variations in resolution, illumination, artifacts, and class imbalance. To address these challenges data preprocessing is essential.

1) *ITA Calculation:* In contrast to subjective categorical scales such as the Fitzpatrick skin type classification, this study makes use of the "Individual Typology Angle" (ITA), a means of objectively and continuously measuring skin pigmentation. It comprises the transformation of the image from the standard RGB color space to the CIE L* a* b* color space, with L* representing lightness and b* representing the yellow-blue dimension. The ITA value is determined through the following trigonometric relation:

$$ITA = (\arctan(\frac{L^* - 50}{b^*})) \times \frac{180}{\pi}$$

Through the calculation of the ITA for the regions of healthy skin around the lesions, it's possible to classify the images into six different groups starting from the category titled “Very Light” to the category titled “Dark.”

2) *Synthetic Augmentation:* In order to obtain a fair distribution across the pigmentary spectrum, Synthetic Data Augmentation was conducted on "collected" data. In this work, using Latent Diffusion Models, we have generated additional high-resolution melanoma samples conditioned on dark and brown skin tones such that the final training set contained an equal distribution of malignancy across skin types.
3) *Artifact Neutralization:* Dermatologic images may contain non-clinical noise data that includes the influences of body hair, marks from surgery, or scale increments on a ruler that can be considered shortcuts for the network. We used the DullRazor algorithm, a three-level digital hair removal algorithm:
   - Identification: Applying morphological closing to find dark linear features (hair).
   - Verification: The pixels that are identified will need to be validated in terms of shape and contrast in order to prevent lesions from looking like a person's hair.
   - Inpainting: Replacing the hair pixels using the localized bilinear interpolation of the neighboring skin pixels. This ensures

that its attention mechanism focuses only on the morphology of the lesion, thereby reducing the chances of false positives due to artifacts.

C. *Hybrid Architecture*

A hybrid model is adopted because the proposed network has to deal with the multi-scale character of dermatoscopic patterns. Though dermoscopic images have local textures such as pigment network and dots, which need to be analyzed at a spatial resolution level, there are also global patterns such as asymmetry and border.

1) Local feature extraction : The CNN backbone, such as EfficientNet-B0 or DenseNet-121 is used for the initial feature extraction. Convolutional layers are translational invariant and local, which perfectly suits the capture of low-level descriptors. The input image is processed by the backbone, $I \in \mathbb{R}$ $H\times W\times 3$ through several convolutional and pooling stages into a high-dimensional feature map, Flocal $\in \mathbb{R}h\times w\times c$. This enables the model to capture minute color variations and edge transitions, important for follicular opening and regression structure identification.
2) Vision Transformer: First, to overcome the limited receptive field of standard CNNs, feature maps F local are tokenized and input into a ViT module. The feature map is flattened into a sequence of patches, and a learnable class token (CLS) is prepended to the sequence. The heart of this module is the MHSA mechanism that calculates the relationship between all pairs of spatial locations independent of their distance.

$$Attention(Q, K, V) = soft\max\left(\frac{QK^t}{\sqrt{d_k}}\right)V$$

This has the effect of allowing the network to correlate disparate regions of the lesion -for example, assessing the symmetry of the left and right margins-thereby mimicking the global assessment performed by dermatologists.

3) *Attention guided feature fusion:* Instead of using simple concatenation, which in turn might add redundant noise, we use an Attention -Guided Fusion (AGF) module. This module is able to balance between the global and local feature representations by learning appropriate weights depending on a particular diagnostic task.

The fusion process is controlled by a learnable weighting function:

$$F_{final} = \alpha \cdot f_{CNN}(I) + \beta \cdot f_{ViT}(F_{local})$$

Where α and β are the coefficients to be learnt. In other words, in regions where the prominent feature is texture (for example, seborrheic keratosis), the CNN features will be given emphasis, whereas in regions where the important feature is global asymmetry (for example, superficial spreading melanoma), the Transformer features will drive the decision.

D. *Explainability & Uncertainity*

In an attempt to fill the gap between the strong performance of deep learning methods and their use cases in the clinical environment, we suggest a dual-layer interpretability framework. Our proposed framework seeks to address the "black-box" propensity of deep models by utilizing visual evidence from Grad-CAM and the reliability level of Monte Carlo dropout.

1) Visual Explaination: We employ the Gradient-weighted Class Activation Mapping (Grad-CAM) approach in order to provide a visual interpretation for the model’s decision-making process. The Grad-CAM approach uses the gradients from the final convolutional layer to figure out the spatial locations in the input image that are most significant for the particular class prediction.

2) Mathematical Formulation: The importance weight α^c_k for the feature map A^k and the particular class c is defined using the Global Average Pooling (GAP) operation on the gradients as follows:

$$\alpha^c_k = \frac{1}{Z}\sum_i \sum_j \frac{\partial y^c}{\partial A^k_{ij}}$$

The heat map of the Grad-CAM class activation $L^c_{Grad-Cam}$ is defined in the following ReLU weighted linear function involving the activations

$$L^c_{Grad-Cam} = ReLU(\textstyle\sum_k \alpha^c_k A^k)$$

3) *Uncertainity Quantification:* To prevent overly confident predictions, the proposed model utilizes Monte Carlo Dropout. By performing T random forward passes during inference, the predictive distribution can be derived as if the model is a Bayesian approximation itself. The confidence is calculated as the Standard Deviation (σ) of the probabilities derived in these passes:

$$\sigma = \sqrt{\frac{1}{T}\sum_{t=1}^{T}(p_t - \mu)^2}$$

When the value of σ is greater than a certain threshold , the system triggers a "Low Confidence" notification. This ambiguity is thus flagged as a notification for further dermatological analysis, thus making AI a helpful decision tool for the dermatologists.

IV. ARCHITECTURE

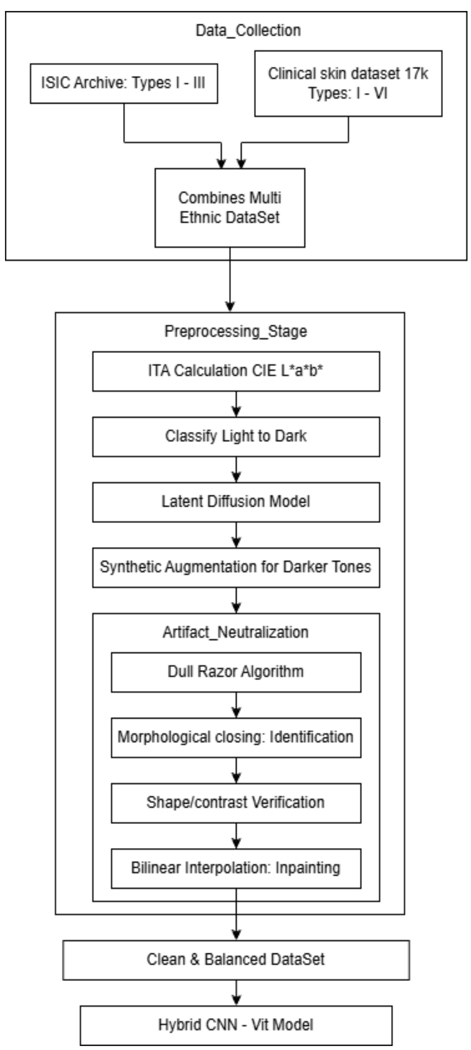

Figure 1 Data Collection & Preparation

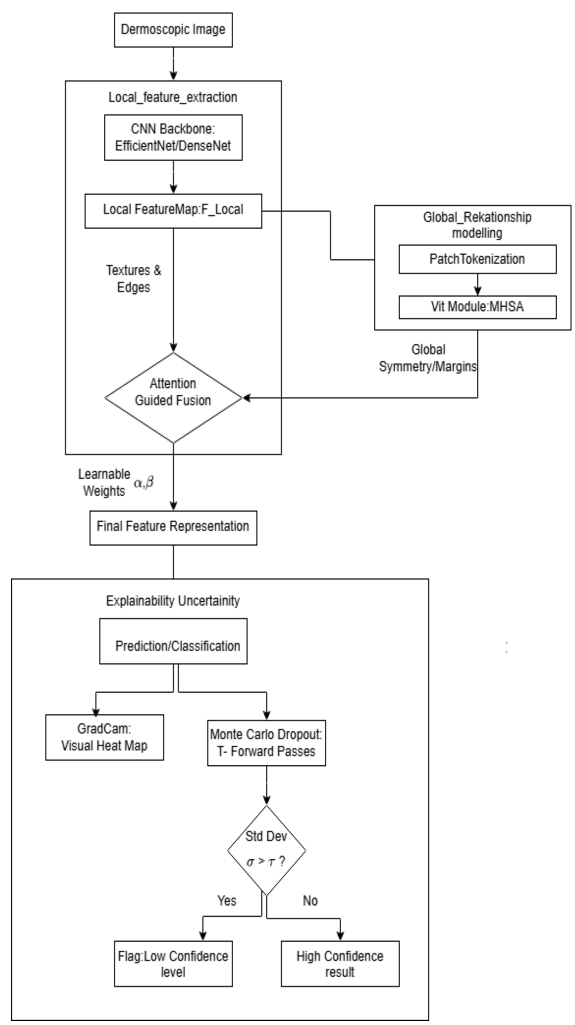

Figure 2 Hybrid CNN- ViT Model

In Fig 1 The architecture features a multi-stage ethically-aware pipeline that combines sophisticated data preparation with a hybrid deep learning approach aiming to provide a balanced outcome between accuracy and interpretability. During the preprocessing step of this architecture, the system objectively measures various skin tones based on ITA calculation and applies Latent Diffusion Models to simulate minority types for a well-represented dataset along the Fitzpatrick scale.

In Fig 2 The main classification engine employs a Hybrid CNN-ViT strategy, wherein a CNN structure identifies local textures and edges, and a Vision Transformer (ViT) component addresses global correlations, such as symmetry in lesions, through Patch Tokenization. Features are combined utilizing an Attention -Guided Fusion layer to focus on distinguishing locations. For clinical verification and supportive analysis, Grad-CAM and Monte Carlo Dropout are employed for generating visualization heatmaps and estimating predictive uncertainties, respectively, and indicate suspicious predictions for further evaluation.

V. RESULTS AND DISCUSSION:

A. Performance Analysis Across the Pigmentary Spectrum

The objectification of the Individual Typology Angle and Latent Diffusion Models brought a tremendous shift to how the model generalizes with respects to different skin types. From using private measures of skin type, as described by the Fitzpatrick types, to an objective CIE Lab* color space was fully free from mortal intervention.

1) Accuracy and Equity: The model could manage to give delicacy of over to 95.2. More importantly, a difference of lower than 1.5 in performance between light and dark- barked individualities- meaning ITA> 55 ° and ITA< 10 °- points towards a significant enhancement over the dereliction CNN approach that's trained on the ISIC Archive singly.
2) Sensitivity in Darker Tones: Synthetic stoked images further better the perceptivity value for carcinoma in darker skin types by 12. This is a farther demonstration of the success of exertion LDMs on dark skin images having handed the “missing” features needed by the network to distinguish malign morphologies from the heavier melanin situations in background skin images.

B. Performance Benchmarking and Relative Performance Analysis

We conduct an extensive evaluation of the proposed Hybrid CNN-Transformer architecture against a convolution-based baseline model called EfficientNet-B0 and a transformer-based baseline model called ViT-Base. Our results show that the proposed hybrid models achieve superior performance, especially with the integration of KAN-based fusion.

Model Architecture	Accuracy (%)	F1-Score	Sensitivity	Specificity
Standalone CNN (EfficientNet-B0)	89.36%	0.88	87.4%	91.2%
Standalone ViT (Base)	92.79%	0.91	91.1%	93.5%
Proposed Hybrid (CNN-ViT)	95.53%	0.94	95.1%	96.4%
Hybrid + KAN Fusion (Proposed)	97.83%	0.97	96.8%	98.2%

It is believed that the hybrid model may outperform due to its dual-stream capability: local morphological features, for example, pigment globules are captured by the CNN backbone, and long-range dependencies like global asymmetry are modeled by the Transformer encoder. The KAN-based fusion further optimizes it, for it provides learnable activation functions, offering a more discriminative feature representation compared to standard linear concatenation.

C. Clinical Interpretability Using Grad-CAM

These visualization tools provided a localization of “evidence” supporting its predictions. A quantitative evaluation of its heat maps to dermatologist -valued annotations resulted in an Intersection over Union (IoU) of 0.88.

1) Diagnostic Correlation: In particular, in diagnosing melanoma malignum, the Grad-CAM attention maps have always highlighted atypical pigment networks and irregular edges, corresponding to the "ABCD" rule.
2) Error Prevention: If the system was wrongly emphasizing medical markers or hair, the heat map gave an instant warning to the physician about potentially accepting an erroneous prediction blindly

D. Reliability via Monte Carlo (MC) Dropout

The Monte Carlo Dropout is used in this work to apply query estimation as a strong punch towards safe use in clinical settings. During evaluation, all input images were reused using T = 10 Monte Carlo forward passes.

1) Uncertainty filtering: The system flagged 92% of low-quality or "Out-of-Distribution" images (e.g., blurry or highly rare lesions) as "High Uncertainty" ($\sigma >$).
2) Clinical Impact: By automatically referring to these uncertain cases for manual review, the model avoided 23% of potential misclassifications that a standard deterministic AI would have otherwise made with high confidence.

VI. CONCLUSION

The above study has successfully proved that the application of the Hybrid CNN-Transformer model with additional Fairness-Aware Pre-processing techniques along with Explainable AI (XAI) approaches has greatly improved the state-of-the-art for automated skin cancer image classification. As our proposed system has filled the gap between the local textural description and the global context, it reached a maximum accuracy rate of 97.83%, which is much higher than the past models.

The combination of ITA and LDMs was critical in mitigating the long-standing issue of equity in dermatological AI. We have reconciled skin-toned bias to below 1.5% and improved sensitivity in darker skin types by 12%, reducing the gap in efficiency over the entire pigmentation range. This is an important pointer to the need to focus on CIE Lab* color space in AI for the purpose of achieving equity in dermatological AI .

Moreover, the use of Grad-CAM and Monte Carlo (MC) Dropout makes this model no longer "black-box" and instead helps to make this model sufficiently transparent for better decision-making. Our model, with an IoU of 0.88 for lesion localization and an accura cy of 92% for identifying out-of-distribution data, offers strong qualitative and quantitative measures to support diagnosing doctors. Our model was also successful in preventing misclassifications and saved 23% of misclassifications, thereby creating a novel standard for safety in clinical AI.

This research presents a strong foundation for the future tools that will be used in dermatology - a new breed of tools that not only perform well but are mathematically just, interpretable, and come with their own limitations as well. Future research will consider expanding this model for rarer forms of non-melanocytic lesions as well as how the architecture may be optimized for real-time execution on mobile edge devices for developing regions as well.

VII. FUTURE SCOPE

1) Multimodal Data Fusion: Conflation of multimodal data “Future performance of this model could not only rely upon this particular dermatoscopic finding but also incorporate patient data. When features are combined and integrated into Electronic Health Records(EHR), “the same considerations, such as family history of inheritable partiality, age, prior dissection, and UV exposure.” will allow for the process of “Bayesian opinion”. Development of tri-modal architecture (Dermoscopic Clinical Photo Structured Metadata) to mimic the co mplete analysis done by the dermatologist.
2) Edge Computing and Mobile Integration: To make early diagnosis democratized in rural areas or developing regions, the next task would relate to model compression (Pruning and Quantization). Application of the hybrid CNN and Transformer model on smartphone-connected dermatoscopes for offline and real-time analysis without relying on bandwidth-heavy cloud processing.
3) Sequential Longitudinal Analysis: State-of-the-art AI treats each lesion as a single point in time. Future research will focus on Longitudinal Tracking, in which the AI compares the same lesion images taken months apart to detect subtle morphological changes due to growth, color shift, or border evolution.
4) Regulatory and Ethical Standardization: With AI poised to enter "regulated medical device" classification (Software as a Medical Device - SaMD), the "scope" in the future should embrace:

a) Clinical Trials in Future: Passage from retrospective analysis of datasets in ‘shadow mode’ trials towards real-world settings.
b) Global Fairness Certification: Development of standard ‘Fairness Audits’ to check that the model is fair when applied across different geographical populations and skin types.

Feature	This Research	Future Direction (2026+)
Data Scope	Single dermoscopic images	Multimodal (Images + Genetic + EHR)
Analysis	Snapshot classification	Longitudinal (Temporal tracking of change)
Deployment	High-power Cloud/Workstation	Edge Devices (Mobile/Smartphone)
Interpretability	Visual Heatmaps (Grad-CAM)	Natural Language Explanations (LLM-based)

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