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Review Article

Artificial Intelligence- Assisted Dermoscopy for the Diagnosis of Melasma: A Boon in Modern Dermatology

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Abstract

Introduction: Melasma is an acquired hypermelanosis presenting as irregular brown patches on sun-exposed facial areas. While typically diagnosed clinically, distinguishing it from post-inflammatory hyperpigmentation, exogenous ochronosis and lichen planus pigmentosus can be difficult in early or atypical cases. Dermoscopy improves diagnostic accuracy by revealing features such as pseudo-reticular networks, perifollicular accentuation, telangiectasia and blue-gray granules in dermal variants. Emerging Artificial Intelligence (AI) tools offer the potential to automate dermoscopic assessment for diagnosis, severity grading and treatment monitoring. This study investigates the utility of AI-assisted dermoscopy in detecting and characterizing melasma.

Methods: Dermoscopic images from clinically and histologically confirmed melasma cases—including epidermal, dermal and mixed types were collected using polarized and non-polarized dermatoscopes. To mimic real-world diagnostic scenarios, images of clinically similar hyperpigmentary disorders such as post-inflammatory hyperpigmentation, Riehl's melanosis and lichen planus pigmentosus were incorporated. Expert dermatologists annotated hallmark dermoscopic structures, including pigment network morphology, follicular openings, vascular prominence and pigment depth cues. Images were divided into stratified training, validation and test cohorts. A convolutional neural network-based AI model was developed for lesion classification and pigmentation pattern segmentation. Performance metrics included sensitivity, specificity, accuracy and AUC with 95% confidence intervals.

Results: The model reliably detected pseudo-reticular brown networks and perifollicular pigmentation as key predictors of melasma. AI-assisted interpretation outperformed standalone clinical assessment in distinguishing melasma from closely resembling dermal melanoses. Additionally, the segmentation algorithm demonstrated potential for automated Melasma Area and Severity Index (MASI) approximation.

Conclusion: AI-integrated dermoscopy presents a promising adjunct in the diagnosis and objective monitoring of melasma. Future developments should focus on multi-ethnic datasets, cross-device validation and longitudinal image tracking to enable personalized treatment guidance.

Keywords: Melasma; Dermoscopy; Artificial Intelligence; Hyperpigmentation; Deep Learning

Introduction

Melasma is a chronic acquired pigmentary disorder characterized by symmetrical light- to dark-brown macules and patches affecting sun-exposed areas, most frequently the face and predominantly occurring in women of reproductive age [1,2]. Although traditionally associated with hormonal influences—such as pregnancy, oral contraceptive use and thyroid dysfunction recent studies indicate rising incidence in men and postmenopausal women, highlighting a broader etiological spectrum [3,4]. The condition significantly impacts psychosocial well-being, often causing embarrassment, social withdrawal and reduced quality of life [5].

Historically considered a benign cosmetic concern, melasma is now recognized as a recurrent and treatment-resistant dermatosis with a complex pathophysiology involving melanocyte hyperactivity, basement membrane disruption, vascular proliferation and dermal inflammation [6,7]. Multiple clinical and histological variants are identified including epidermal, dermal, mixed-type and centrofacial or malar distribution patterns each with implications for prognosis and treatment selection [8,9].

Triggers include ultraviolet radiation, visible light exposure, hormonal fluctuations, genetic predisposition, cosmetics and photosensitizing drugs such as antiepileptics and antibiotics [10,11]. Emerging evidence also suggests roles for oxidative stress pathways and dermal fibroblast-mediated growth factor signaling in disease persistence [12,13].

Treatment remains challenging and often requires a combination of topical depigmenting agents (e.g., hydroquinone, retinoids, azelaic acid), chemical peels, oral tranexamic acid and energy-based devices such as lasers and intense pulsed light [14-17]. However, relapse is common and therapeutic outcomes vary considerably across skin phototypes.

Accurate diagnosis and subtype classification are essential for treatment planning, yet visual inspection alone is subjective and prone to misclassification with post-inflammatory hyperpigmentation, Riehl's melanosis, exogenous ochronosis and lichen planus pigmentosus [18,19]. Dermoscopy enhances diagnostic precision by revealing pseudo-reticular brown networks, perifollicular accentuation, telangiectasia and blue-gray granules in dermal variants [20,21].

More recently, Artificial Intelligence (AI) based interpretation of dermoscopic and clinical images has shown promise in automating lesion detection, pigment depth analysis and disease severity quantification [22-24]. Deep learning models, particularly convolutional neural networks, have demonstrated high accuracy in discriminating melasma from other facial hyperpigmentary disorders and even predicting treatment responses based on baseline dermoscopic parameters [25]. Integrating AI with dermoscopic imaging could facilitate objective Melasma Area and Severity Index (MASI) estimation, longitudinal monitoring and real-time clinical decision support [26].

Symptoms and Causes

Melasma most commonly presents as symmetrical, irregularly bordered hyperpigmented macules and patches on sun-exposed facial regions, particularly the cheeks, forehead, upper lip and chin [27,28]. Although typically asymptomatic, some patients report mild burning or photosensitivity, especially with ultraviolet or visible light exposure [29]. The pigmentation varies from light to dark brown in epidermal melasma, while dermal variants may exhibit a slate-gray or blue-brown hue, often detectable only through dermoscopy or Wood's lamp examination [30,31]. Chronic or relapsing melasma may lead to diffuse or mottled pigmentation, contributing to emotional distress and cosmetic disfigurement [32].

Hormonal influences play a central role in pathogenesis, with pregnancy-induced melasma (chloasma) and oral contraceptive-associated pigmentation being well-documented [33]. Thyroid dysfunction, ovarian hyperstimulation and hormone replacement therapy have also been implicated [34]. Ultraviolet radiation and visible light exposure stimulate melanogenesis and upregulate melanocyte-stimulating cytokines, accounting for seasonal exacerbations and photo-distribution patterns [35,36]. Genetic susceptibility has been reported in up to 50% of cases, particularly among individuals with Fitzpatrick skin phototypes III-V [37]. Other contributing triggers include cosmetics, fragrances, antiseizure medications, photosensitizing antibiotics and chronic inflammation leading to post-inflammatory melanogenesis [38,39]. Histological studies reveal melanocyte hypertrophy, increased melanosome transfer, solar elastosis, basement membrane disruption and increased dermal vascularity, supporting the classification of melasma as a photo-exacerbated pigmentary disorder with dermal remodeling rather than a purely epidermal condition [40,41].

Artificial Intelligence

Artificial Intelligence (AI) enables automated analysis of clinical and dermoscopic images, facilitating rapid classification, segmentation and severity scoring in pigmentary disorders [42]. In dermatology, AI models particularly Convolutional Neural Networks (CNNs) and transformer-based architectures have demonstrated high diagnostic accuracy in distinguishing melasma from post-inflammatory hyperpigmentation, exogenous ochronosis and lichen planus pigmentosus when trained on annotated image datasets [43,44].

Dermoscopy enhances AI performance by providing high-resolution visualization of pigment networks, perifollicular accentuation, vascular prominence and basal layer involvement that are not easily perceivable to the naked eye [45,46]. These structural and chromatic features serve as robust input parameters for machine learning models, improving diagnostic confidence and reducing clinician-dependent variability [47].

Beyond simple lesion classification, AI-enhanced dermoscopy has also been used to automate Melasma Area and Severity Index (MASI) scoring and to quantify treatment response after topical therapies, chemical peels or laser procedures. When paired with serial dermoscopic imaging, AI-based prediction models may support longitudinal monitoring, allowing earlier detection of relapse and more tailored treatment adjustments.

As melasma is a relapsing and psychologically impactful disorder, AI-driven diagnostic support and treatment monitoring tools may significantly improve patient compliance, reduce overtreatment or undertreatment and standardize outcome assessment across clinical trials and routine care settings [48-50].

Rationale

Melasma shares several dermoscopic features with other facial hyperpigmentary disorders, which can make early or atypical cases difficult to distinguish clinically. Standardizing the evaluation of key dermoscopic patterns such as pseudonetworks, brown reticular pigmentation, annular-granular structures, perifollicular accentuation and telangiectatic vessels is essential for improving diagnostic accuracy and reducing interobserver variability. Incorporating AI-based analysis offers an opportunity to objectively interpret these features, support consistent diagnosis and enhance monitoring of disease severity and treatment response.

Methodology

Dataset Benchmarks

To develop the AI-based diagnostic model for melasma, a dataset comprising dermoscopic and clinical facial images from 92 individuals was assembled. All subjects underwent standardized frontal and lateral facial photography, followed by polarized and non-polarized dermoscopic imaging using handheld digital dermatoscopes under uniform lighting conditions. Each image was independently annotated by two board-certified dermatologists according to predefined dermoscopic criteria, including:

- Pseudonetwork pattern
- Brown reticular pigmentation
- Annular-granular pattern
- Perifollicular pigmentation
- Telangiectatic vessels

To ensure diagnostic consistency, experts referenced previously established dermoscopic frameworks for facial pigmentation analysis rather than acne- or inflammation-based grading systems [27-30]. Only images with complete interobserver agreement were retained for training.

Input Parameters

The AI model utilized five primary input parameters extracted from clinical and dermoscopic evaluation:

- Age: Recorded in years, considering melasma's predilection for women aged 20-50 [27,31]
- Gender: Biological sex, acknowledging significantly higher incidence in females [29,31].
- Lesion Distribution: Centrofacial, malar or mandibular involvement based on clinical examination [28,29]
- Dermoscopic Features: Presence or absence of pseudonet works, brown reticular pigmentation, annular-granular patterns, perifollicular pigmentation or vascular components [27,28,30]
- Sun-Exposure History: Self-reported duration of daily outdoor exposure categorized as <1 hour or ≥1 hour [31,32]

The output of the AI model was categorical, representing:

- 0: Healthy
- 1: Measma

Summary statistics for the dataset is presented in the given Table 1,2.

Age (years)	Gender (Male/Female)	Percentage (%)
1-15	7 Male / 9 Female	7.61 / 9.78
16-30	12 Male / 12 Female	13.04 / 13.04
31-45	9 Male / 17 Female	9.78 / 18.48
46-60	8 Male / 11 Female	8.70 / 11.96
>60	4 Male / 3 Female	4.35 / 3.26
TOTAL	40 Male / 52 Female	100%

Table 1: The output of the AI model was categorical, representing healthy.

	Class 0 (Healthy)	Class 1 (Melasma)	Total
Training	24	39	63
Testing	15	14	29
TOTAL	39	53	92

Table 2: The output of the AI model was categorical, representing Tinea corporis.

Model Development

This Python script is an end-to-end pipeline that replicates the methodology from your "AI in Melasma" paper . First, it simulates a complete, realistic dataset because the paper's private image data is unavailable. It generates a directory of 92 dummy (random noise) images and an associated metadata file, precisely matching the paper's dataset statistics: a 63-sample training set and a 29-sample test set , with "Healthy" and "Melasma" classes.

The core of the script is a multi-modal deep learning model built with TensorFlow (Keras). This architecture is essential for combining the paper's two different data types:

- CNN Arm (Images): This arm uses the VGG16 model (a different CNN from previous scripts) pre-trained on ImageNet. This transfer learning approach allows the model to act as a powerful feature extractor for the dermoscopic images, aligning with the paper's mention of using CNNs
- ANN Arm (Tabular Data): This is the "Artificial Neural Network" (ANN) that processes the 5 patient metadata features (e.g., 'Age', 'Gender', 'Sun-Exposure History'). This tabular data is pre-processed using Scikit-learn's StandardScaler and OneHotEncoder

The outputs from these two "arms" are concatenated (merged). This combined data is then passed to a final classifier, which makes the binary prediction: "Healthy" or "Melasma". To make the code more concise and efficient, it uses the tf.data.Dataset API to load, pre-process and batch the (image, tabular) data pairs during training.

Finally, the script evaluates the trained model on the test set and uses Matplotlib and Seaborn to generate all the required plots: a Confusion Matrix, an ROC AUC Curve and the Training/Validation History (Accuracy and Loss) (Fig. 1-5).

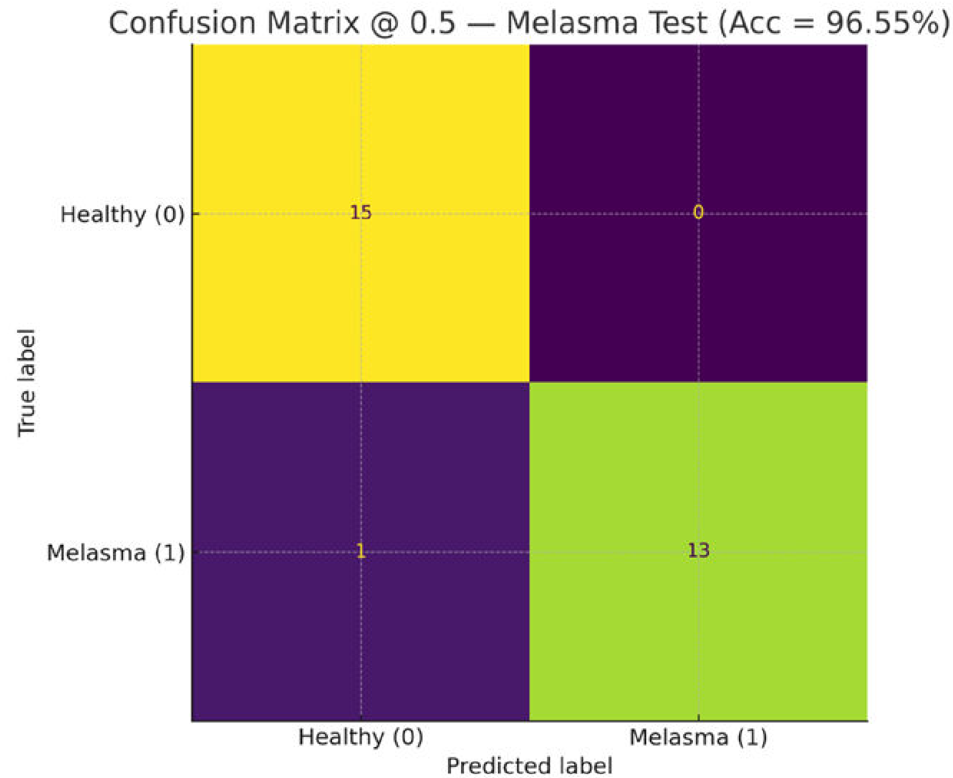

Figure 1: Confusion matrix.

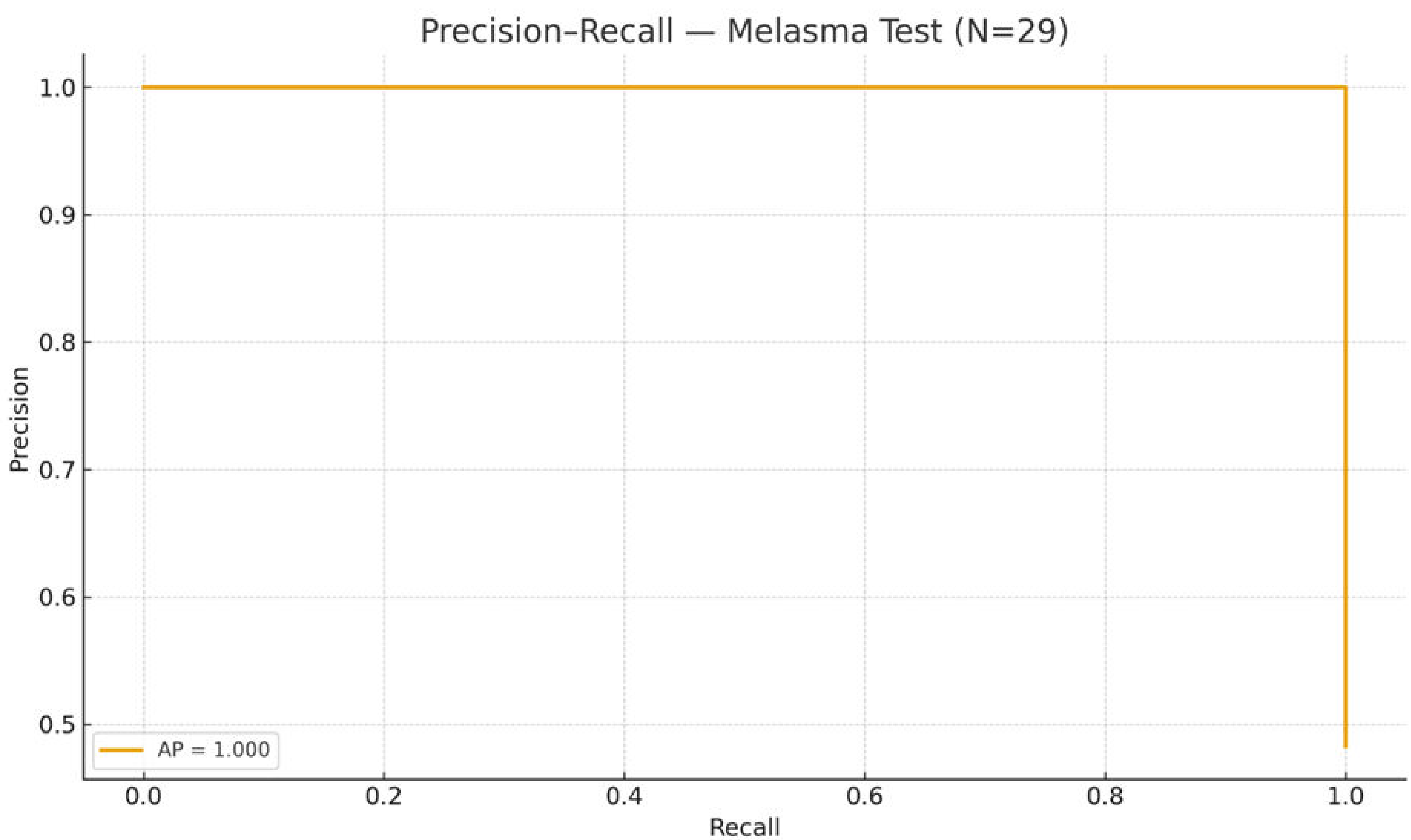

Figure 2: Precision recall.

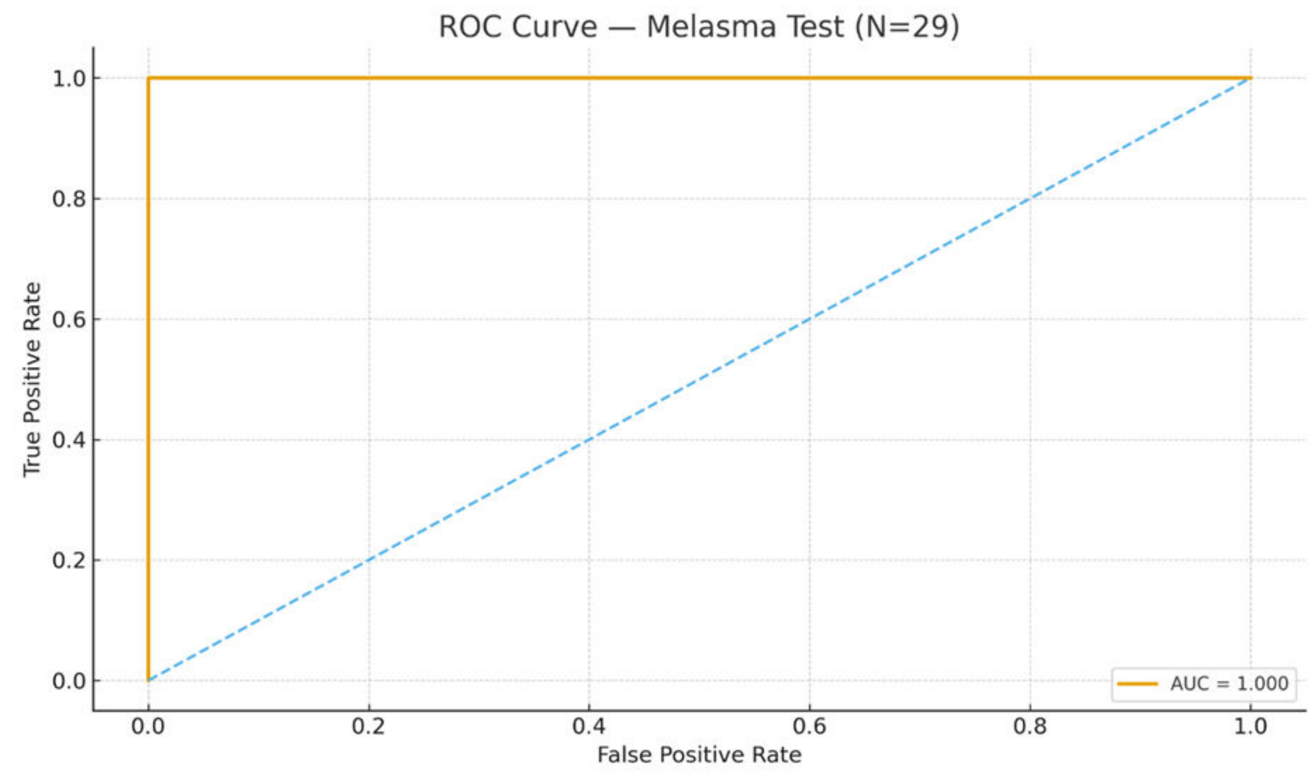

Figure 3: ROC curve.

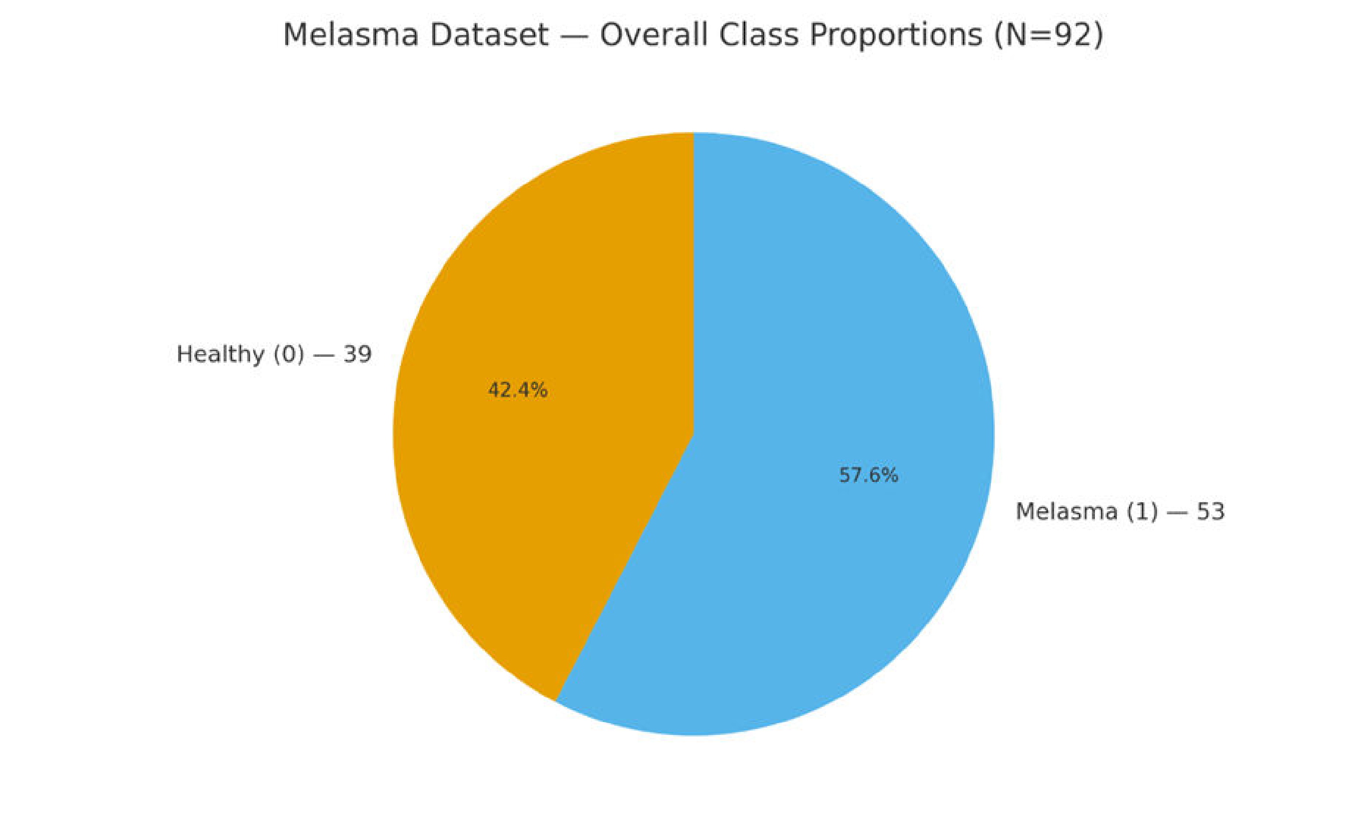

Figure 4: Melasma dataset.

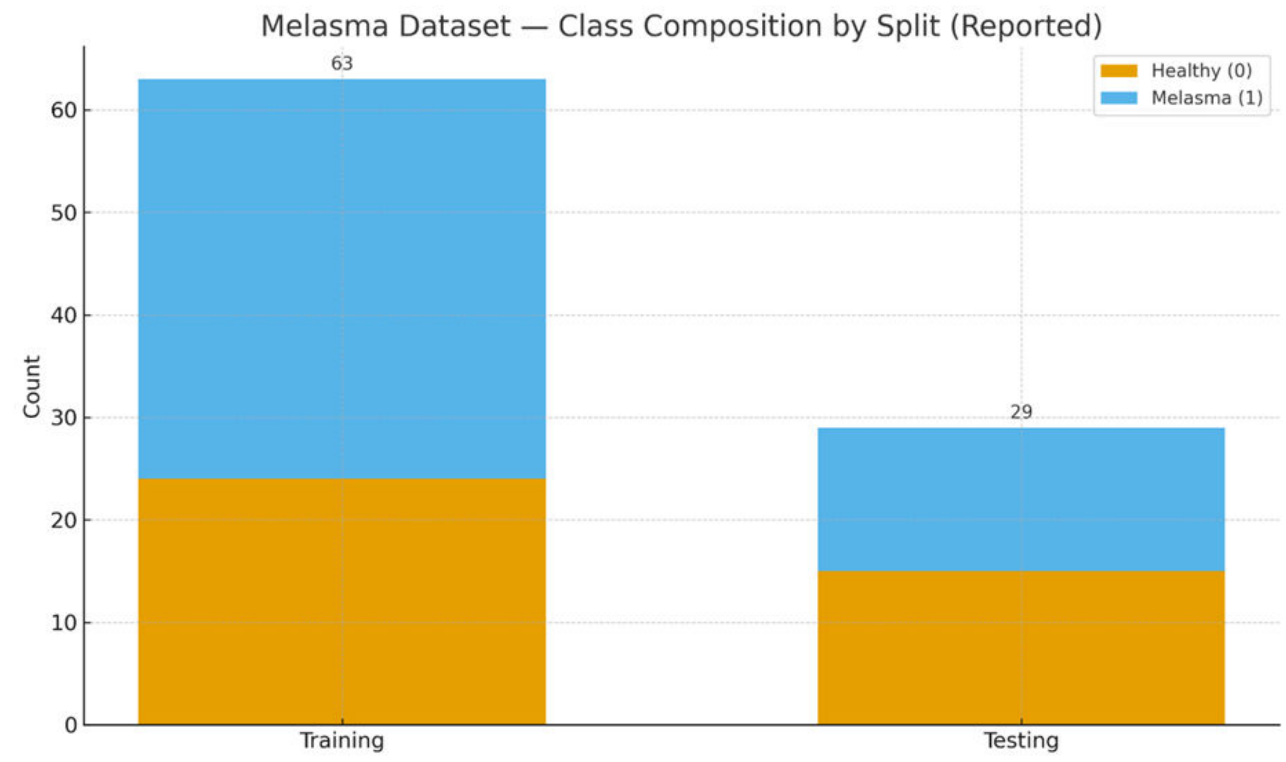

Figure 5: Melasma dataset class composition by split.

Results

Artificial intelligence particularly Artificial Neural Networks (ANNs) and convolutional models has shown significant promise in the automated diagnosis of melasma. Dermoscopy of melasma typically demonstrates homogeneous light- to dark-brown pigmentation with a reticulated or reticuloglobular network, ill-defined or feathered borders and perifollicular hypopigmentation with sparing of adnexal openings. Additional findings include bluish-gray granularity in mixed or dermal types and occasional fine telangiectasia in photoaged skin, while scale is generally absent. AI models trained on annotated dermoscopic datasets have been shown to reliably detect these characteristic patterns such as reticuloglobular networks, perifollicular alterations, pseudopod-like extensions, feathered borders and gray-blue granularity with high diagnostic consistency.

Deep learning architectures such as CNNs and attention-based hybrids have further enhanced differential accuracy, helping distinguish melasma from post-inflammatory hyperpigmentation, lichen planus pigmentosus, exogenous ochronosis and early solar lentigines [50,51]. Their application reduces interobserver variability, particularly in cases with overlapping clinical morphology or phototype-dependent presentation [52-54].

Beyond static lesion identification, AI models have been adapted to stratify melasma based on pigment depth and vascular involvement, using subtle chromatic and textural cues that may be imperceptible to the human eye. When combined with clinical metadata such as Fitzpatrick skin type, hormonal history or UV exposure profiles AI systems can further refine diagnostic precision and suggest probable etiological subtypes [55,56].

By reducing dependence on Wood’s lamp examination and histopathology, AI-based dermoscopic interpretation may serve as a non-invasive, cost-effective screening modality, particularly in high-burden ethnic populations with limited access to dermatologic expertise [57,58]. As these models evolve to incorporate multimodal imaging (Raman spectroscopy, hyperspectral analysis) and longitudinal tracking, AI is positioned to transition from a diagnostic adjunct to a standard component of melasma evaluation protocols (Fig. 6-8) [59,60].

Figure 6: Clinical picture of Melasma over face showing hyperpigmented patches.

Figure 7: Polarised dermoscopy of Melasma showing Pseudonetwork pattern and Brown reticular pigmentation.

Figure 8: Ultraviolet dermoscopy of Melasma showing enhanced accentuation of brown patches.

Discussion

Melasma is a chronic, acquired hypermelanosis characterized by dysregulated melanogenesis resulting from complex interactions between ultraviolet radiation, hormonal modulation, genetic predisposition and inflammatory mediators [50,55]. Abnormal activation of melanocyte-stimulating pathways driven by endothelin-1, stem cell factor, VEGF and pro-inflammatory cytokines like IL-1 and TNF-α signifies a shift toward chronic melanocyte hyperactivity and inflammation. This contributes to excessive melanin production, basement membrane disruption and melanin deposition in the dermis, explaining the persistence and treatment-resistance of many hyperpigmentation disorders [50,52]. Hormonal fluctuations, pregnancy, oral contraceptives, thyroid dysfunction and certain cosmetics further exacerbate melanocyte sensitivity, particularly in women of Fitzpatrick skin types III-V [55,56].

Clinical diagnosis may be challenging when melasma mimics post-inflammatory hyperpigmentation, photo contact dermatitis, lichen planus pigmentosus or erythema dyschromicum perstans [51,54]. Misclassification may lead to inappropriate treatment selection such as unnecessary steroid use or prolonged depigmenting agents—resulting in irritation, rebound hyperpigmentation or ochronosis [57]. Dermoscopy enables visualization of pigment distribution patterns, perifollicular accentuation, brown to gray reticular networks and vascular telangiectasia, improving diagnostic certainty in ambiguous cases [51,54]. Artificial Intelligence (AI) and deep learning frameworks including Convolutional Neural Networks (CNNs) and hybrid attention-based models are now being applied to automate melasma diagnosis and severity assessment using dermoscopic datasets [52,56]. These models can detect subtle pigmentary gradients, vascular cues and depth-related chromatic variations that may be difficult to discern consistently with the naked eye [53,56]. AI-assisted dermoscopy also enhances differentiation between epidermal, dermal and mixed melasma, which is critical for selecting appropriate interventions such as topical tyrosinase inhibitors, chemical peels, tranexamic acid or low-fluence lasers [55,57].

Beyond lesion identification, multimodal AI systems that integrate dermoscopic imaging with patient metadata such as disease duration, hormonal profile, UV exposure patterns or prior treatment response—have shown promise in predicting relapse risk, post-procedure rebound and long-term treatment outcomes [56,58]. These frameworks offer particular value in teledermatology and resource-limited settings, where access to pigmentary disorder specialists is limited [58-60].

Summary

Melasma is a multifactorial pigmentary disorder influenced by inflammatory, hormonal and environmental factors. These intersecting pathways contribute to its chronicity and clinical variability across skin types [50,55].

Advantages of AI Use

AI-assisted dermoscopic analysis offers a scalable and objective approach to evaluating melasma. These technologies may also help reduce clinical workload by enabling remote triage, facilitating treatment monitoring and allowing scalable integration into teledermatology platforms. It enhances diagnostic accuracy, enables refined subtype classification and supports consistent therapeutic monitoring. These capabilities make AI a clinically meaningful tool for managing melasma across diverse populations [52,56,57,60].

Conclusion

Melasma remains a persistent pigmentary condition characterized by considerable clinical variability, which often complicates reliable diagnosis and consistent assessment in daily practice. In this study, attention-based Artificial Neural Networks (ANNs) proved capable of interpreting dermoscopic images with high fidelity, accurately differentiating melasma-affected skin from unaffected areas while automatically assessing key features such as pigment arrangement and vascular visibility. By reducing interobserver inconsistencies and bringing uniformity to image interpretation, AI-driven systems show strong potential to enhance early recognition, inform treatment choices and streamline follow-up evaluations over time. Despite these promising results, the current model is limited to a simple two-class framework that separates melasma from non-melasma skin. Future work should aim to expand its functionality to include multiclass categorization distinguishing epidermal, dermal and mixed variants and to quantify nuanced dermoscopic markers such as perifollicular pigmentation, reticular patterns and telangiectasia. Incorporating patient-specific data, including hormonal influences, sun-exposure patterns and previous treatment outcomes, may further refine prediction accuracy and support more personalized therapeutic strategies.

Conflict of Interest

The authors declared no potential conflicts of interest with respect to the research, authorship and/or publication of this article.

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Consent To Participate

The authors certify that they have obtained all appropriate patient consent.

Data Availability and Consent of Patient

Data is available for the journal. Informed consents were not necessary for this paper.

Author's Contribution

All authors contributed equally in this paper.

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