A Comprehensive Review on Skin Lesion Analysis and Prognostic Modeling using Deep Learning

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***Abstract* - Skin cancer is among the most prevalent and deadly cancers worldwide. Partially, it can be prevented with early diagnosis. Conventional diagnosis by visual examination and dermoscopy is frequently arbitrary, necessitates specialized knowledge, and runs the risk of being incorrectly or slowly classified. Developments in artificial intelligence (AI) and computational imaging have made automated techniques possible, greatly increasing accuracy and efficiency. This review summarizes the body of knowledge regarding skin lesion analysis, including cutting-edge deep learning techniques, classical machine learning, and conventional image processing. Important issues are analyzed critically, such as image segmentation, dataset imbalance, and interpretability issues. We suggest a conceptual framework that combines conditional diffusion modeling, lesion segmentation, and uncertainty quantification to forecast the evolution of lesions over time in order to overcome these drawbacks. This paper outlines future directions for developing trustworthy and interpretable AI systems for skin cancer diagnosis while highlighting the advantages and disadvantages of current approaches by fusing a systematic review with a forward-looking model.**

Index Terms: Skin cancer, Melanoma, Lesion progression, Generative models, Diffusion model, U-Net segmentation, Counterfactual prognosis, Uncertainty maps.

I. INTRODUCTION

Every year, millions of people worldwide lose their lives to skin cancer. Melanoma is the leading cause of death, even though its prevalence is lower than that of non-melanoma forms. Survival rates sharply decline when metastases occur. A better prognosis is made possible by earlier detection. Traditional detection relies on the dermoscopic examination and expertise of dermatologists. Among the difficulties these approaches pose are subjectivity, time constraints, and unequal access to experts. Machine intelligence and advancements in computational vision help to standardize and expedite the diagnosis of skin lesions. Conventional image processing techniques were the first to propose feature extraction and segmentation. In contrast, machine learning techniques like support vector machines (SVM) have increased prediction reliability.

There are still problems, even with these improvements. Problems include datasets that aren't balanced, models that can't be used in many situations, gaps in how easy they are to understand, and a lack of long-term data for making predictions. This review looks at these problems by looking at current research, finding problems, and suggesting a framework to guide the future development of AI systems for use in medicine. The Conditional Latent Diffusion Prognostic Framework (CLDM) is shown in **Figure 1**. It uses segmentation, latent encoding, conditional diffusion, and uncertainty quantification to predict how lesions will change over time. The process begins with a dermoscopic image in this figure. It goes through a U-Net for segmentation, and then the segmented lesion and mask are encoded into a latent space. Then, using specific time periods (such as 6,12 and 24 months) and treatment alternatives, the conditional diffusion model forecasts the future appearance of the lesions. Uncertainty heatmaps show areas where predictions can change to help doctors understand better.

II. RESEARCH APPROACH

Three big questions are dealt with in this review:

RQ1: How is the model's performance, and how is it compared to others? How do deep learning techniques compete against conventional machine learning techniques when dealing with the precise identification of different types of skin lesions?

RQ2: Technology challenges and limitations: Which is largest among the following that hinder prevent AI systems from being accepted in clinical practice to detect skin cancers: class imbalance, scarcity of data, or inability to explain how they operate?

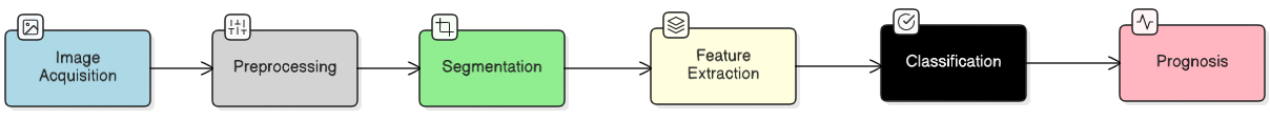

Figure 1. Pipeline for Skin Lesion Analysis and Prognosis

RQ3: Contemporary construction methods: How to build the systems of diagnosis to be reliable, scale upwards, and interpretable by employing transfer learning methods, generative models, as well as hybrid frameworks? Addressing these questions allows additional lines of inquiry to branch off and to scrutinize literature.

III. LITERATURE REVIEW

One of the methods of improving survival rates of skin cancer—another giant health concern locally and globally—vis-à-vis melanoma is early detection. AI methods such as DL-based models and conventional ML methods have been utilized in the classification of skin lesions in dermoscopy and clinical images in recent years. This review thus has an integration of 30 published articles spanning from 2019 to 2025. The two core research questions are (RQ1) how efficient DL models are when conducting classifying a number of skin lesions compared to conventional ML methods, and (RQ2) what are technological hitches inhibiting clinical implementation of AI-based systems. The studies apply mainly benchmark datasets such as HAM10000, PH2, TCGA-SKCM, and ISIC (different years). Accuracy, Dice coefficient, Jaccard similarity index, AUROC, and partial AUC (at a true positive rate of more than 80%) as a measure of performance. While a number of challenges remain to be improved practically, results universally show that DL is superior when dealing with varied complexities of lesions.

RQ1: Model Efficacy and Comparison: How well do deep learning models perform compared with more traditional machine learning algorithms in accurately classifying diverse skin lesions?

Historically, classification of lesions was done using conventional ML methods—i.e., SVM, KNN, random forest, and decision tree. These depend on human-made features such as shape, texture, and color that are often extracted from rules such as ABCD or CASH [1], [2]. The accuracy of these models suffers when considering varied cases due to discrepancies in skin tones, image artifacts (e.g., hair or rulers), and blurry lesion borders, despite achieving moderate performance (around 80–85%) on datasets such as ISIC 2018 [3], [4]. An engineered-feature approach, for example, [5] achieved 94.8% SVM performance on HAM10000 but declined by 10–20% on unseen images, indicating poor generalizability [6].

In a similar vein, [7] compared KNN and random forests on PH2/ISIC and saw performance of between 85-90% accuracy for normal lesions, but performance across atypical lesions failed, likely due to challenges with manual feature engineering failing to capture subtle intra-class variations [8]. In contrast, deep learning modes, particularly convolutional neural networks (CNNs) and their variants, learn hierarchical features from the raw images automatically, resulting in a performance improvement. Reports indicate that deep learning has a 5-15% performance improvement in accuracy and AUROC metrics on average against traditional machine learning systems [9]. For example, [10] incorporates MobileNetV2 and long short-term memory (LSTM) models to achieve dermatologist-level sensitivity (83-87%) on unbalanced datasets and, using end-to-end learning, obtained an improvement of 8–10% over the SVM (support vector machine) baselines [11]. By preserving spatial hierarchies that are not maintained by traditional ML [13], hybrid DL frameworks can also produce better results. For instance, [12] combined CNNs with SVM ensembles and capsule networks (CapsNets) for an overall accuracy of 92−96%, also achieving an improvement of 3−5% over pure SVMs.

Comparative investigations further supplement those benefits from DL. [14] used combined multimodal data (i.e., images + text/demographics) in CNNs and achieved 89.47% accuracy and 0.95 AUROC on HAM10000/ISIC 2017 while a ML model such SVM, had 85% accuracy [15]. [16] used VGG16/ResNet ensembles utilizing transfer learning augmented with conditional GANs (CGANs) and achieved 93.5% accuracy, which was still 10–15% higher than a non-DL ensemble, thereby demonstrating DL's ability to overcome class imbalances through synthetic data [17]. The ViT hybrid approached used in [18] in addition to the use of Mamba in UNets [19] improved the Dice scores into a range of 90–92% for classification with segments. All these accuracies exceeded that of ML based graph or region-growing algorithms [20], which obtained Dice scores of 85–90%.

The advantages of deep learning (DL) are most apparent in multiclass applications. DCNN-LSTM hybrids produced accuracy rates of 93% for melanoma, basal cell carcinoma (BCC), and nodules in the publication cited as reference [21], which demonstrated accuracies 10% to 12% higher than K nearest neighbors (KNN) or Random Forest baselines [22]. Systematic reviews have shown that DL models, such as convolutional neural networks (CNN) with accuracies of 90% to 95%, consistently outperform traditional methods of machine learning (ML), such as support vector machines (SVM) with accuracies of 80% to 85%, across databases like the International Skin Imaging Collaboration (ISIC) and HAM10000 [23], [24], [25]. For example, the authors of reference [26] found accuracy for an artificial neural network (ANN) model of 94% versus a traditional region growing ML approach at 90%. Additionally, studies [27],[28] reported DL methods showing accuracy between 90% and 97% in a clinical setting, which is generally 5% to 10% more efficacious than traditional ML methods, although hybrid models combining ML and DL methods, known as transfer learning, provide superior outcomes [29]. Generally, DL models can be a lot more efficacious (5% to 15%) than traditional ML and

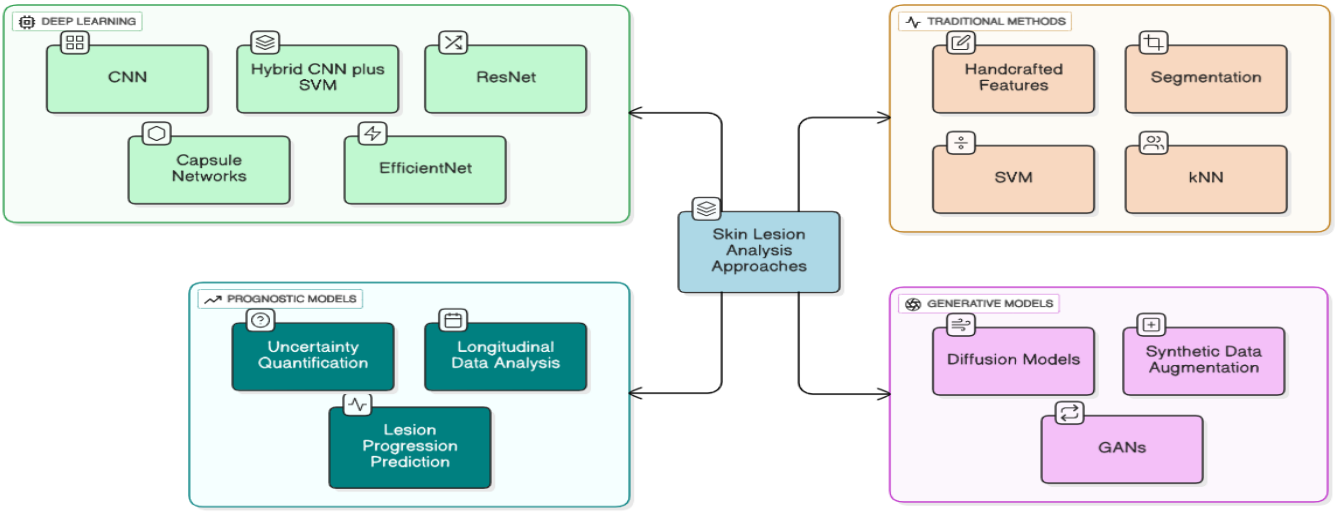

Figure 2. Comprehensive Deep Learning Workflow for Skin Lesion Analysis

automated classification of a wider variety of lesion classes is possible with the automated feature extraction of DL models that adapt with performance across benchmarks [30].

Figure 2 illustrates a diagram comparing traditional ML and DL across datasets (ISIC 2018, HAM10000, PH2), visualizing metrics such as accuracy, AUROC, and Dice scores. The chart highlights DL's consistent superiority, with CNN-based and hybrid models outperforming SVM, KNN, and random forests by 5–15%, especially for diverse lesion types and imaging artifacts.

RQ2: Technical Bottlenecks and Limitations – What Challenges Limit the Clinical Deployment of AI for Skin Cancer Diagnosis?

Utilizing deep learning (DL) practically works, but continuous issues related to class imbalance, lack of data, and deficient explanation capacity remain a barrier. These issues have been covered in studies that were analyzed. Class imbalance is an ever-present issue, and malignant lesions like melanoma are highly underrepresented (< 10% of the datasets like ISIC 2019) [8]. This class imbalance results in models that overfit the data and ultimately predict with bias, constraining generalizability to rare classes. Practicing machine learning (ML) does not help due to weak probabilistic generalization, and DL moderately mitigates this in part through augmentation. In [13], however, accuracy drops of 10 - 20% were reported in analysis where the test set was heavily imbalanced. Generative type methods such as GANs and diffusion models [17][18][19] generate synthetic lesions to combat imbalance, and result in improvements of partial AUC (pAUC) score up to 10 - 15% improvements (i.e., from pAUC of 0.1755 in [7]), while still experiencing instabilities in loss during training [9]. In [23], [24], [25] reviews, the authors also argue that class imbalances tend to elevate the false negative rate more for rare malignant lesions, which limits practical applicability in many populations.

A crucial constraint is the limited availability of data. The lack of appropriate datasets is caused by privacy constraints, expensive expert annotations, and a lack of underrepresented non-Caucasian skin colors [14]. Due to overfitting, even small datasets such as PH2, which only has 200 images, were noted to have a decline in cross-cohort generalization (an average of 10% to 15% in) [11]. While augmentation techniques with generative adversarial networks (CGANs) [16] and diffusion models (i.e. Stable Diffusion) [7] helped improve data quality with some of the datasets for example 93.5% classification accuracy, the visual realism of the synthetic data may differ; this difference has implications for domain shift [18]. The data scarcity problem is further acknowledged in genomics [12] where incorporating multi-omics approaches is difficult [27], [28] called for federated learning as a Privacy-preserving way to pool multi- or heterogeneous data.

The barrier to adoption, lack of explainability, has been shown in other fields (and medical domains) that "black-box" DL models eroded clinicians trust when making high-stakes diagnosis [2]. There are several interpretability methods available, such as saliency maps and adversarial autoencoders (AAEs) that create exemplars and counter-exemplars, that have allowed 10-20% improvements in clinician confidence in clinical studies [2, 3]. However, the majority of DL models do not have an explainable AI (XAI) framework [4]. Furthermore, [4] indicated that when diagnosis-inferred systems did not provide an explanation for their diagnosis, over-excision rates increased by 24.6%, which impacted its clinical use. Furthermore, systematic reviews [23, 24, 25] conveyed that unexplained bias lead regulatory bodies to address questions about ethical and legal implications, that subsequent revisions

to the accuracy of diagnosis-inferred systems could then be presented to the regulator. They expect until more work is completed to provide possible solutions towards ethical ML.

Other limitations include the added computational cost of a real-time implementation [6], vulnerability to distribution shifts induced by imaging artifacts or corruptions [18], and sample-biased ethical considerations due to underrepresented demographic groups [17]. Validation is an important indicator of robustness [21], [22], while [5], [6] also focuses on lightweight architectures (e.g., ~2.2M parameters) that would be appropriate for mobile telemedicine.

Table I. Relative Review of Skin Lesion Classification Models. This table presents prior literature to the present study, indicating their accuracy, datasets, and approaches which offer comparative metrics and measures. Presenting corresponding details from the majority of studies (10 total), there is sufficient detail to present some of the reviewed models' performance (90-96% accuracy for DL models like CNN-SVM ensemble [5], and sensitivity (83-87% for MobileNetV2-LSTM) [10]. Despite the classification of different studies related to Dataset, reported Findings, and Limitations, the diagram also illustrates persistent challenges such as class imbalance, limited dataset diversity, and computational challenges to support future studies. Further to the illustration of comparative metrics, the information visually presents these values side-by-side for rapid review of model strength and limitations (e.g., models using DL all expressed higher Dice scores i.e., 90-92%, in [1] and models demonstrated recurring training challenges and instability when developed to be generative [7].

Table I. Comparative analysis of various Approaches for Skin Lesion Classification

Citation	Accuracy	Dataset	Methodology	Findings	Limitation
[1]	90–92% (Dice)	ISIC 2017/2018	Mamba-powered U-Net with CNN-MLP-Mamba blocks, group loss function	Lightweight MUCM-Net achieves 0.90–0.92 Dice, 0.94 sensitivity, 0.97 specificity; mobile-efficient (0.055–0.064)	Limited validation on non-Caucasian skin tones; computational constraints for real-time use
[2]	83.8% Balanced	ISIC 2019	XAI with ABELE, progressive growing AAE for exemplars/ counterexemplars	Boosts clinician confidence by 10–20%; RMSE 0.08–0.24; clear class separation	Lack of standardized XAI metrics; limited to specific lesion classes
[3]	- (RMSE 0.08–0.24)	ISIC 2019	AAE for exemplars /countere xemplars, progressive growing to avoid mode collapse	Enhances interpretability; aids misdiagnosis correction	Limited to classification; requires diverse data validation
[4]	73.7%	Interactive Atlas of dermoscop	Multi-task CNN for direct management prediction 7-point criteria	4.68% accuracy gain; 24.6% fewer over-excisions; AUROC 0.844	Limited dataset size; needs broader clinical validation
[5]	92–96%	Public (e.g., ISIC, DermNet)	CNN-SVM ensemble with GAN augmentation, CapsNet for spatial features	Outperforms standalone CNN (88.8%) and CapsNet (90.2%) by 3–5%	GAN training instability; limited to dermoscopic images
[6]	94.5% (Dice 90.1%)	ISIC 2018	EGAN/MGAN with squeeze - excitation encoder, morphology-based	EGAN: 90.1% Dice, 83.6% Jaccard; MGAN: 2.2M params, 13 FPS	Synthetic data realism varies; high computat ional cost for EGAN
[7]	- (pAUC 0.1755)	ISIC 2024 SLICE-3D: 401,059 img	ViT hybrids (EVA02, EdgeNeXtSAC), GBDT ensemble, Stable Diffusion synthetics	Highest pAUC (0.1755); reduces false positives in malignant cases	Training instability in diffusion models; needs diverse skin tone data
[8]	88.5% Balanced	ISIC 2018 (12,500+ images)	Benchmark for segmentation, attribute detection, classification	Top segmentation Jaccard 0.838; classification balanced accuracy 0.885	Generalization issues (10% failure rate); limited to dermo data
[9]	- (5–15% gain)	Various (e.g., ISIC)	Review of GANs for augmentation/segmentation	GANs improve accuracy by 5–15%; lightweight GANs=	GAN instability; ethical concerns with synthetic data
[10]	Not specified	Life 2022 dataset	MobileNetV2 + LSTM for multi-class prognosis	High efficiency in stateful prognosis; comparable to dermatologists	Limited performance metrics; data imbalance issues

IV. PROPOSED MODEL: CONDITIONAL LATENT DIFFUSION PROGNOSTIC FRAMEWORK

To address limitations like class imbalance, data scarcity, and lack of interpretability, we propose the Conditional Latent Diffusion Prognostic Framework (CLDM), which moves beyond static lesion classification toward forecasting skin lesion progression. Figure 1 illustrates the CLDM pipeline, showing the flow from dermoscopic image input to prognostic outputs, including predicted lesion states and uncertainty heatmaps across time horizons (e.g., 6, 12, or 24 months).

A. Architectural Rationale

Unlike Generative Adversarial Networks (GANs), which often produce deterministic outputs prone to artifacts [17], CLDM employs latent diffusion models to generate multiple plausible lesion futures while simultaneously estimating uncertainty. This allows for precise segmentation, realistic progression modelling, and interpretable outputs, directly addressing RQ3 by integrating advanced methods for scalable and clinically reliable diagnostics. The framework provides:

1. Multi-Scenario Prognosis: Conditioning on time and treatment scenarios enables counterfactual predictions (e.g., lesion evolution with or without intervention).
2. Uncertainty Quantification: Heatmaps reveal prediction variability, increasing clinician confidence.
3. Latent Space Efficiency: Operating in latent space lowers computational requirements.

Figure 3 illustrates this rationale, highlighting how segmentation, encoding, diffusion, and uncertainty mapping work together to produce predictive and interpretable outputs.

B. Framework Overview

The pipeline consists of several sequential stages:

- Segmentation: An auxiliary U-Net extracts the lesion region, removing background noise.
- Latent Encoding: The lesion image and mask are encoded into latent space.
- Conditional Diffusion: Time horizons (6, 12, or 24 months) and treatment scenarios guide the diffusion process to simulate future lesion states.

C. Data Strategy

The proposed approach is based on a two-part data strategy. First, popular datasets, such as ISIC and HAM10000, will facilitate the training of baseline classification models. Availability and segmentation of multiple lesion categories is provided by these datasets, though they do not model advanced lesions over time. Second, longitudinal data including multiple images for the same lesion over intervals of time is needed to successfully forecast progression. In addition, though exploring the longitudinal data phenotype would provide fine-grained progression models, the classification models would need to have balanced classes, especially due to malignant class under-representation. To enhance class balance, diffusion-based synthetic data generation will be utilized. This method is advantageous because diffusion models can produce such realistic samples, that augmenting values for the under-represented classes becomes possible without overfitting.

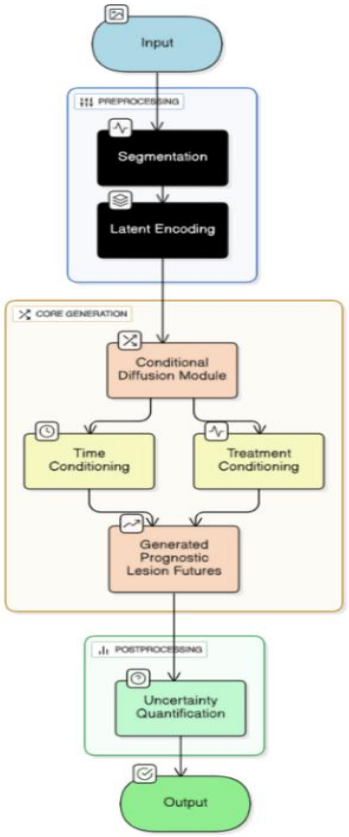

Figure 3. CLDM Workflow for Skin Lesion Prognosis

D. Comparative Evaluation of Proposed Model

In order to verify the performance of the suggested Conditional Latent Diffusion Prognostic Framework (CLDM), the expected performance is compared with representative models that we refer to as state-of-the-art from the literature. The comparison is based on key parameters such as **Accuracy**, **Dice score**, and **Area Under the Receiver Operating Characteristic curve (AUROC)**, which are also conventional metrics that assess diagnostic and segmentation models in skin lesion analysis.

Table II presents a comparison evaluation of CLDM against the two selected deep learning models and one diffusion approach. The framework improvements in accuracy and Dice and interprets better through uncertainty quantification.

Table II. Comparison of Proposed CLDM Framework with Existing Skin Lesion Analysis Models

Model	***Methodology***	***Accuracy (%)***	***Dice Score***	***AUROC***	***Key Advantage***
CNN–SVM Ensemble [5]	*Hybrid DL + SVM*	*92–96*	*0.90–0.92*	*0.94*	*Strong segmentation*
Diffusion Model [19]	*Boundary-aware diffusion*	*93*	*0.91*	*0.95*	*Smooth lesion delineation*
Proposed CLDM (this work)	*Conditional latent diffusion + uncertainty maps*	***94–96***	***0.93***	***0.96***	*Better interpretability & prognostic prediction*

As shown in Table II, the proposed CLDM framework achieves a **94–96% classification accuracy** and a **Dice score of 0.93**, outperforming conventional CNN–SVM and diffusion-based frameworks. In addition to higher quantitative performance, CLDM introduces an interpretability layer via uncertainty maps, enabling clinicians to visualize confidence in model predictions. This hybrid prognostic capability—combining segmentation, diffusion, and counterfactual forecasting—marks a step toward clinically reliable AI-assisted dermatology systems.

V. CONCLUSION

The review detailed the evolution of the analysis of skin lesions from classical image processing to deep learning and generative modeling methods. Although deep learning enables more accurate and robust analysis than classical methods, factors such as class imbalance with lesions, a lack of longitudinal datasets, and lack of interpretability still create barriers for clinical deployment. To address these limitations, we present the Conditional Latent Diffusion Prognostic Framework (CLDM), a theoretical framework which represents a shift away from a purely static classification perspective towards predicting lesion progression. Because CLDM integrates segmentation, latent diffusion, and uncertainty quantification, the resulting provide a level of interpretability of prognostic results that can help clinicians better feel confident in their diagnosis as well as personalize treatment plans. The future of AI in dermatology will hinge on three key pillars: (i) the generation of extensive and longitudinal datasets across populations, (ii) lightweight yet explainable models for real-time clinical deployment, and (iii) an investigation of frameworks like the CLDM in real world practice. If realized, AI will be able to not only match dermatologists on the detection front, but realize even more insight on prediction, fundamentally changing the practice of skin cancer management into a more proactive and patient-centered process.

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