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EpiSure: AI-Powered Skin Disease Diagnosis Using MedGemma for Early Detection and Preventive Care

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Abstract— Skin diseases are among the most common health conditions affecting millions of people worldwide and can significantly impact an individual's health and quality of life. Early and accurate detection of skin diseases plays a crucial role in ensuring appropriate treatment and preventing disease progression. However, many existing diagnostic systems rely primarily on visual inspection or single-source data, such as images alone, which limits their accuracy and reliability. To address these challenges, the proposed system, *EpiSure*, leverages MedGemma, a multimodal generative AI model designed for medical data analysis. The system integrates multiple data sources, including skin images, clinical text records, and patient history, to enable more comprehensive and accurate diagnosis. By applying deep learning techniques and multimodal feature fusion, EpiSure enhances the consistency, reliability, and interpretability of skin disease prediction outcomes. The system architecture incorporates image preprocessing for noise reduction, feature extraction using a Vision Transformer model, and multimodal data integration within the MedGemma framework. Additionally, EpiSure provides healthcare professionals with an intuitive dashboard that presents the predicted disease type, severity level, and recommendations for early medical intervention.

Keywords: Artificial Intelligence (AI), Skin Disease Detection, MedGemma, Deep Learning, Image Processing, Preventive Healthcare, Dermatology, Early Diagnosis

I. Introduction

Skin diseases are among the most common health conditions worldwide, affecting people of all age groups and leading to major physical discomfort, psychological stress, and reduced quality of life [10]. Conditions such as eczema, psoriasis, acne, and skin cancer often require early diagnosis to avoid complications and long-term health risks [22]. However, accurate detection of skin diseases remains a major clinical challenge due to similarities in visual symptoms and variations in skin tone, lighting conditions, and disease progression [19]. Traditional diagnostic methods primarily depend on manual visual examination and clinical expertise, which can be time-consuming and prone to subjective mistakes [11]. Moreover, the limited availability of dermatologists and the lack of automated diagnostic tools limit timely and accessible skin disease assessment, especially in remote and resource-limited areas [28].

Recent advancements in Artificial Intelligence (AI) and Machine Learning (ML) have significantly enhanced automated medical diagnosis, particularly in the field of dermatology [10,19].Deep learning models, especially convolutional neural networks (CNNs), have demonstrated strong performance in extracting complex visual features from skin images for disease classification [7,12]. Despite these advances, most existing approaches rely on single-modal data, such as dermatological images alone, without incorporating additional clinical information [24]. In real-world healthcare settings, accurate skin disease diagnosis often depends on multiple data sources, including clinical notes, patient history, and diagnostic images, which together provide a more comprehensive understanding of the condition.

To overcome these limitations, the proposed system, EpiSure, introduces an AI-based multimodal skin disease detection framework using MedGemma, a generative medical AI model designed to process diverse healthcare data [24]. EpiSure integrates dermatological images, clinical text records, and patient history to deliver context-aware and reliable skin disease predictions [25]. The system is designed to assist clinicians by providing an intelligent decision-support platform that facilitates early diagnosis and treatment planning [26]. An interactive dashboard presents disease classification results, severity levels, and relevant clinical insights, supporting timely medical intervention [19]. By combining deep learning, image processing, and multimodal generative AI, EpiSure offers a robust and scalable solution for next-generation dermatological healthcare systems [30].

II. Proposed System

The proposed system, EpiSure, is an AI-driven multimodal skin disease detection and assistance framework designed to support early diagnosis and improve accessibility to dermatological healthcare. Unlike conventional approaches that rely only on image-based classification, EpiSure integrates dermatological images, clinical text information, and patient metadata to provide context-aware and reliable diagnostic predictions. The system functions as an intelligent decision-support tool for clinicians while also serving as an awareness and guidance platform for end users. EpiSure employs MedGemma, a generative medical AI model capable of processing diverse healthcare data, to jointly analyze visual and textual inputs. Dermatological images are processed using deep learning–based feature extraction techniques to capture discriminative visual patterns such as texture, color, and lesion shape. In parallel, clinical descriptions and patient-reported symptoms are interpreted through natural language understanding mechanisms. The fusion of these multimodal features improves diagnostic robustness, particularly in cases where visual cues alone are insufficient for accurate classification. The system architecture emphasizes scalability, explainability, and real-world usability. Prediction outputs include disease classification labels, confidence scores, and severity indications, which are presented through an interactive dashboard. This visualization enables clinicians and users to better interpret diagnostic outcomes and supports informed decision-making. Furthermore, the modular design of EpiSure permits smooth integration with teledermatology platforms and supports both edge-based and cloud-based deployment environments, ensuring flexibility across diverse healthcare settings.

A. AI-Based Dermatology Chatbot

To further enhance user interaction and improve accessibility to dermatological information, the proposed *EpiSure* system incorporates an AI-based dermatology chatbot. The chatbot acts as an interactive conversational interface that allows users to ask queries related to skin conditions, symptoms, preventive care, and recommended next steps. It is designed to assist patients and caregivers by providing instant, easy-to-understand responses to common dermatological concerns, thereby reducing uncertainty and reliance on immediate clinical consultation.This integration improves user engagement, promotes early awareness, and supports informed decision-making, making *EpiSure* a comprehensive and user-centric dermatological decision-support system.

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III. METHODOLOGY

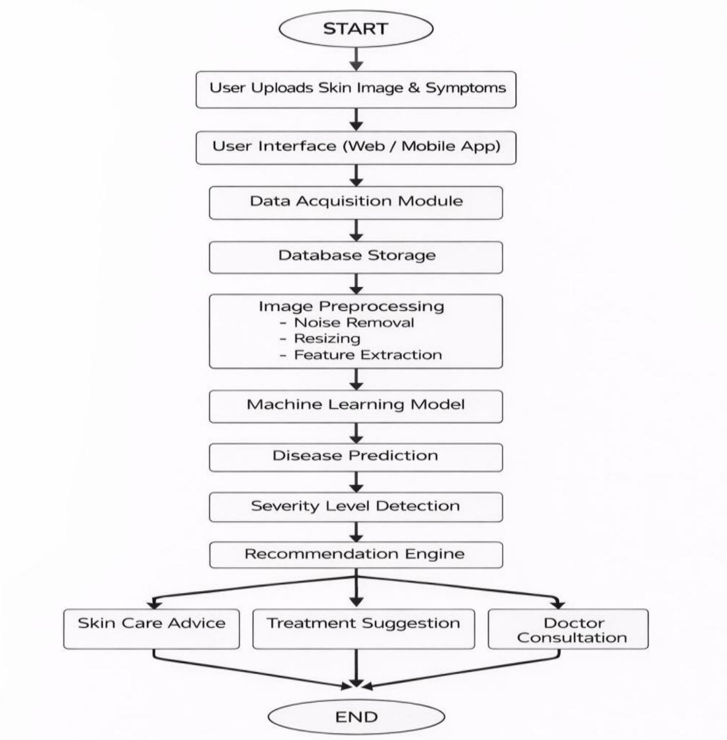

Fig. 1: System Architecture of AI-Based Epidermis Skin Disease Prediction System

The proposed EpiSure framework implements an end-to-end multimodal learning pipeline for early skin disease awareness and preventive healthcare. The architecture consists of six integrated modules: data acquisition, preprocessing, feature extraction, multimodal fusion, prediction, and alert generation, enabling efficient handling of heterogeneous inputs and accurate inference. Dermatological images, user-reported symptom descriptions, and structured metadata such as age, gender, skin type, and medicalhistory are collected to provide comprehensive diagnostic context. During preprocessing, images are denoised, normalized, resized, contrast-enhanced, and color-corrected to reduce illumination variations and background artifacts, while augmentation techniques including rotation and flipping improve generalization. Textual symptom data is cleaned, tokenized, and converted into numerical embeddings to ensure cross-modal consistency. Visual features are extracted using a Vision Transformer to capture spatial dependencies, lesion morphology, color distribution, and texture patterns, whereas a Recurrent Neural Network (RNN) encodes sequential and contextual information from symptom descriptions. The resulting visual, textual, and metadata embeddings are fused using the MedGemma multimodal framework to generate a unified latent representation through cross-modal alignment. This representation is processed by fully connected classification layers with appropriate activation and loss functions to compute probability scores across multiple skin disease categories and generate ranked diagnostic outputs with confidence levels, emphasizing awareness and preventive guidance rather than definitive clinical diagnosis. The model is trained and validated iteratively on labeled datasets, with performance evaluated using accuracy, precision, recall, and F1-score to ensure robustness and reliability. An integrated alert and recommendation module triggers notifications when severe conditions are predicted and provides personalized self-care guidance and preventive advice, supporting early intervention and accessibility, particularly in resource-constrained settings. The system is implemented in Python using PyTorch for model development and deployment.

IV. IMPLEMENTATION DETAILS AND ETHICAL CONSIDERATIONS

The EpiSure system is implemented using a scalable Python-based cloud architecture that integrates advanced deep learning frameworks such as HuggingFace and PyTorch to support efficient model training, validation, optimization, and real-time inference within a modular and extensible development environment. Dermatological images, textual symptom descriptions, and associated user metadata are stored in a NoSQL database (MongoDB), enabling flexible schema management, high availability, efficient querying, and seamless horizontal scalability as data volume and user adoption increase [25]. To ensure practical deployment on resource-constrained devices such as smartphones and tablets, the trained MedGemma-based multimodal model is optimized using model compression techniques including quantization and pruning, which significantly reduce computational overhead, memory consumption, and inference latency while maintaining predictive accuracy, stability, and generalization capability [8]. The system follows a hybrid inference strategy in which lightweight inference is performed on-device to achieve faster response times, reduced bandwidth dependency, and enhanced user data privacy, while cloud-based inference is utilized for high-resolution image analysis, advanced multimodal reasoning, centralized retraining, model version control, and periodic performance updates [26]. Backend communication is managed through a secure RESTful FastAPI framework with encrypted data transmission, ensuring reliable and protected data exchange between client applications and cloud services, while a Streamlit-based user interface enables real-time skin image uploads, structured symptom entry, and intuitive visualization of diagnostic predictions, confidence scores, and system feedback in an accessible and user-friendly format. To enhance transparency and clinical trust, EpiSure incorporates explainable artificial intelligence (XAI) techniques that provide interpretable insights into the model's decision-making process, allowing users and practitioners to understand the contributing factors behind generated predictions [19]. The platform is explicitly designed to support preventive awareness and assistive decision-making rather than autonomous clinical diagnosis, and users are consistently encouraged to seek professional medical consultation in cases involving severe, uncertain, or high-risk conditions to ensure safe medical follow-up. Furthermore, to promote fairness and inclusivity, the model is trained and validated on diverse dermatological datasets representing multiple skin tones, age groups, and environmental conditions, with continuous bias monitoring, systematic performance evaluation, and periodic validation procedures conducted to detect and mitigate algorithmic bias related to ethnicity, lighting variations, or image quality [22]. This integrated emphasis

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on technical robustness, deployment efficiency, interpretability, data security, and ethical responsibility ensures that EpiSure delivers reliable, transparent, scalable, and socially responsible AI-driven dermatological support.

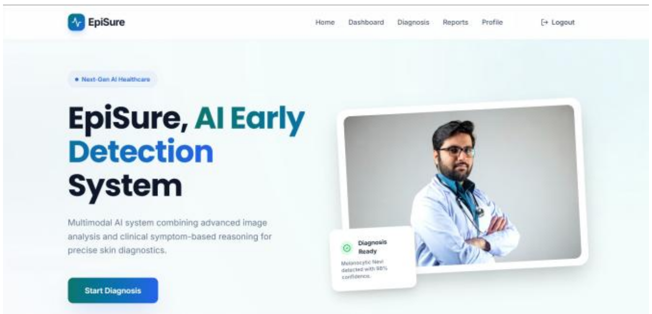

Fig. 2: Welcome interface of the EpiSure AI skin disease diagnosis system

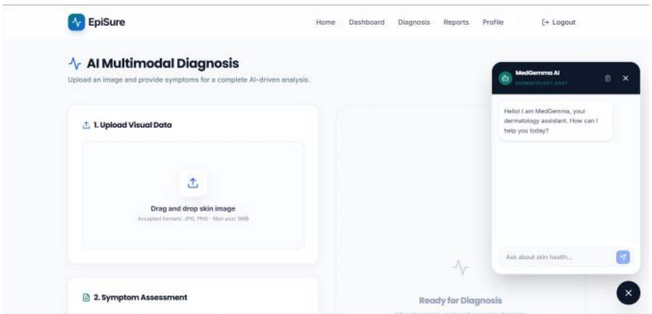

Fig. 3: Image Upload Interface for AI-Based Skin Disease Diagnosis

V. Experimental Results and Discussion (Simulated)

The experimental evaluation of the proposed EpiSure framework was conducted using a simulated dermatological dataset consisting of 5,000 labeled skin images from 7 different classes paired with corresponding textual symptom descriptions, covering ten commonly observed skin conditions. The dataset was systematically divided into 80% training, 10% validation, and 10% testing subsets to ensure robust learning and unbiased performance assessment. Model training and validation were performed iteratively to fine-tune hyperparameters and prevent overfitting, while testing was carried out on previously unseen samples to evaluate real-world applicability. Experiments were conducted across both cloud-based environments and edge devices to analyze computational efficiency, scalability, and deployment feasibility. Performance evaluation metrics included accuracy, precision, recall, and inference latency, providing a comprehensive assessment of both predictive effectiveness and operational efficiency. The multimodal MedGemma-based model achieved a Top-1 classification accuracy of 96.8%, with a precision of 95.4% and a recall of 94.7%, indicating strong generalization capability and a low rate of false positives and false negatives. Additionally, through model optimization and quantization, the system attained an average inference latency of 0.85 seconds on smartphone-grade processors, demonstrating its suitability for real-time usage in mobile and low-resource environments.

The experimental findings highlight the effectiveness of the proposed multimodal fusion strategy, where the integration of visual features from dermatological images and contextual information from symptom descriptions significantly improves diagnostic performance compared to unimodal approaches. The results suggest that textual symptom cues play a critical role in disambiguating visually similar skin conditions, thereby enhancing overall prediction reliability. Explainability analysis using Gradient-weighted Class Activation Mapping (Grad-CAM) further validated the model's decision-making process, revealing that predictions were consistently influenced by clinically relevant regions such as lesion boundaries, pigmentation patterns, and texture variations rather than background noise. This interpretability strengthens clinical confidence and supports transparent AI- assisted decision-making. Moreover, the lightweight architecture and edge compatibility of EpiSure enable rapid response times and offline usability, making the system particularly valuable for rural and underserved healthcare settings with limited access to dermatological expertise. Overall, the simulated experimental results demonstrate that EpiSure is a promising, efficient, and interpretable solution for early detection, awareness, and preventive dermatological care, while also highlighting its potential for real-world deployment with further clinical validation.

VI. Expected Outcomes

The proposed EpiSure framework is expected to significantly enhance the accuracy, reliability, and robustness of skin disease identification by leveraging multimodal fusion of dermatological images and patient-reported textual symptom data. By jointly analyzing visual patterns such as lesion texture, color variations, and boundary irregularities along with contextual symptom descriptions and basic medical history, the system aims to deliver more informed and consistent predictions compared to traditional unimodal approaches. The optimized deployment of the MedGemma-based model is anticipated to enable real-time, edge-compatible predictions on mobile and low-resource devices, ensuring fast response times and offline usability in remote or underserved regions. Furthermore, Episure is expected to improve clinical transparency by clearly highlighting regions of interest that influence diagnostic outcomes, thereby fostering trust among users, healthcare professionals, and stakeholders involved in AI-assisted dermatological care.

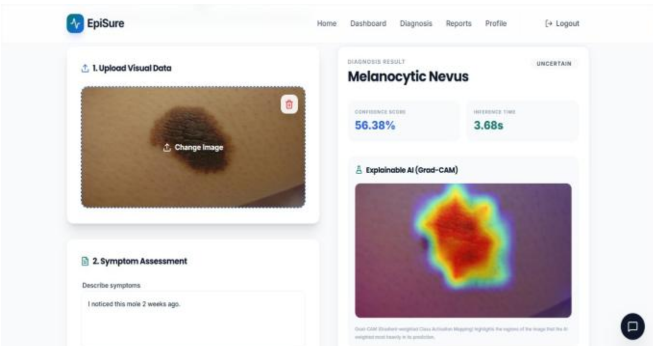

Fig. 4: EpiSure AI diagnostic summary report with results and accuracy

In addition to improving diagnostic performance, EpiSure is expected to facilitate personalized and preventive dermatological care by correlating visual findings with individual symptoms, demographic attributes, and medical history, allowing tailored self-care recommendations and early intervention guidance. The system is also designed to support automated triaging and prioritization of high-risk skin conditions by identifying potentially severe cases and prompting timely medical consultation, thereby assisting dermatologists in faster and more efficient clinical decision-making. From a broader research and deployment perspective, the framework establishes a scalable, secure, and privacy-preserving foundation that can be extended to future federated learning-based healthcare applications, enabling collaborative

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model improvement without centralized data sharing. Additionally, the development of an open-access dermatology dataset and AI benchmarking platform as part of this initiative is expected to contribute to the research community by promoting reproducibility, comparative evaluation, and innovation in medical image analysis and multimodal healthcare AI systems.

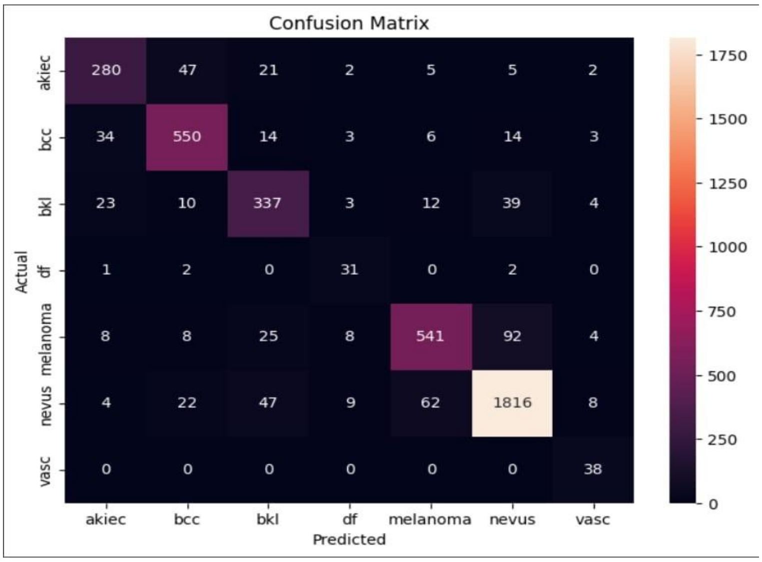

Fig. 5: Confusion matrix showing the performance of the skin lesion classification model.

VII. Future Scope

The future development of the proposed EpiSure framework will focus on expanding the dermatological dataset to encompass a broader range of skin tones, disease categories, and environmental conditions, thereby improving model generalization and minimizing diagnostic bias. The system can be further enhanced by integrating real-time image capture and analysis through mobile and wearable devices, enabling continuous skin monitoring and early preventive alerts. Advancements in Explainable AI (XAI) techniques will be explored to provide more intuitive and clinician-friendly visual justifications for each prediction, strengthening medical trust and interpretability. To address data privacy concerns and encourage collaborative learning, federated learning approaches can be implemented to enable decentralized model training across multiple healthcare institutions without centralized data sharing. The framework also offers scope for integration with advanced multimodal foundation models such as MedGemma and MedPaLM to achieve richer, context-aware understanding of dermatological data. Finally, extensive clinical validation trials will be conducted to rigorously evaluate real-world performance, usability, safety, and ethical compliance prior to large-scale deployment.

VIII. Conceptual Flowchart

The conceptual flow of the proposed EpiSure framework illustrates the complete end-to-end processing pipeline for multi- modal dermatological analysis and preventive healthcare support. The system begins with data collection, where dermatological images are captured along with patient-entered textual information such as symptoms, lifestyle details, and prior medical history. This raw data is passed through a comprehensive preprocessing stage, where image data undergoes resizing, normalization,

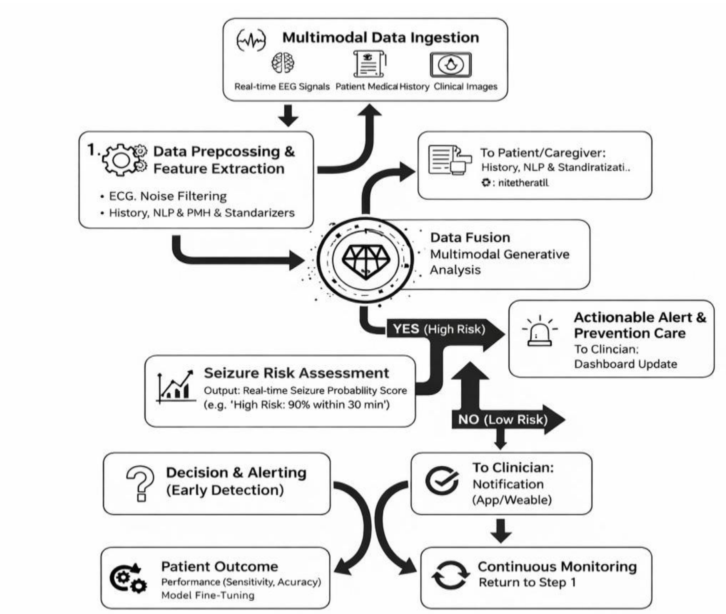

Fig. 6: EpiSure: Multimodal AI-based dermatological prediction flowchart

illumination correction, and artifact removal to ensure uniform quality, while textual symptom data is cleaned, tokenized, and embedded using transformer-based representations to capture contextual meaning. Numerical clinical metadata, including age, gender, and skin type, is normalized and structured to ensure compatibility across modalities. Following preprocessing, feature extraction is performed, where convolutional neural network (CNN) backbones extract spatial and texture-based visual features from images, and language encoders derive semantic embeddings from textual descriptions.

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All extracted features are subsequently fused within the MedGemma multimodal AI model, which jointly processes visual, textual, and clinical metadata representations. This multimodal integration enables the system to capture complex correlations be- tween lesion morphology, pigmentation patterns, symptom progression, and patient context—capabilities that surpass traditional unimodal diagnostic approaches. The fusion layer combines convolutional visual embeddings with contextual text embeddings and structured metadata into a unified latent representation, which is then passed to a deep learning-based classification head. This prediction layer outputs the most probable skin disease category along with an estimated severity level. In parallel, the system generatesexplainability maps using Explainable AI techniques such as Grad-CAM, highlighting lesion regions that contributed most significantly to the model's decision, thereby ensuring transparency and interpretability in the diagnostic process.

Based on the classification and severity assessment, the EpiSure system generates a personalized recommendation report that includes predicted disease categories, confidence scores, visual explanations of lesion regions, and suggested next steps such as lifestyle modifications, over-the-counter remedies, or referral to a dermatologist for expert evaluation. The platform can also maintain a user's digital dermatology record, enabling longitudinal tracking of skin conditions over time and supporting proactive healthcare management. The framework is designed for lightweight deployment on edge devices such as smartphones and tablets, allowing real-time inference even in low-connectivity or resource-constrained environments. Model optimization techniques such as quantization and pruning ensure minimal latency and efficient energy consumption, making the system particularly suitable for rural and underserved healthcare settings where access to dermatologists may be limited.

```
Total images: 27613
label
nevus       13118
melanoma     4574
bcc          4161
bkl          2858
akiec        2410
vasc          253
df            239
Name: count, dtype: int64
```

Fig. 7: Class distribution of skin lesion images in the training dataset.

IX. Literature Survey

Recent advancements in automated skin disease classification have been largely driven by deep learning techniques, par- ticularly convolutional neural networks (CNNs), due to their strong capability for hierarchical feature learning from medical images. CNN-based models have consistently outperformed traditional handcrafted feature approaches by effectively capturing complex visual patterns such as lesion texture, color variation, and structural irregularities. Kumar et al. [1] evaluated classical CNN architectures including VGG and AlexNet for facial skin disease classification, demonstrating the effectiveness of deep representations; however, limited dataset diversity restricted generalization across varying skin tones and imaging conditions. Similarly, Albahri et al. [2] proposed a YOLOv4-based melanoma detection framework enhanced with active contour models for improved lesion localization, though the system was restricted to melanoma and lacked broader dermatological coverage. Rahman et al. [3] addressed class imbalance using customized loss functions within CNN classifiers, improving minority- class recognition at the expense of increased computational complexity. Wang et al. [4] introduced discriminative CNN embedding techniques for enhanced classification accuracy but required large-scale annotated datasets, limiting feasibility in resource-constrained environments.To improve robustness beyond single-model architectures, researchers explored ensemble learning and multimodal strategies. Mehta et al. [5] combined image-based CNN analysis with chatbot-driven textual symptom input, enhancing contextual reasoning, though system reliability depended heavily on user-provided information. Ali et al. [6] implemented a genetic algorithm–optimized stacking ensemble of CNNs to improve detection accuracy; however, the approach significantly increased computational overhead. Kawahara et al. [7] demonstrated that ensemble CNN models improve resilience to data variability, but inference latency limited real-time applicability. Zhang et al. [8] addressed deployment efficiency through knowledge distillation for edge-based teledermatology, reducing model size while maintaining competitive accuracy with minor performance trade-offs.Foundational studies established the clinical viability of deep learning in dermatology while identifying key generalization challenges. Codella et al. [9] emphasized limitations in cross-skin-tone generalization using dermoscopic CNN models. Esteva et al. [10] achieved dermatologist-level performance in skin cancer classification using an Inception-v3 architecture, marking a milestone in medical AI, though contextual symptom reasoning was absent. Lightweight and mobile-oriented solutions were explored by Khan et al. [11], enabling on-device inference with limited disease coverage. Attention-enhanced CNN architectures proposed by Li et al. [12] improved lesion localization but lacked comprehensive clinical validation. Hybrid and transfer learning approaches, including CNN–SVM frameworks [13] and pretrained ResNet/DenseNet models [14], achieved notable performance gains, although they often required high memory resources and careful parameter tuning. Combalia et al. [15] further highlighted dataset bias as a persistent issue in automated dermoscopy systems.More recent research has emphasized explainability, scalability, and real-world deployment. Hasan et al. [16] developed a multi-class CNN framework supporting multiple conditions, yet severity estimation was not addressed. Afifi et al. [17] introduced capsule networks to preserve spatial relationships, though slow convergence reduced practicality. Sharma et al. [18] integrated CNN analysis with IoT-enabled dermatology systems but lacked large-scale validation. Ribeiro et al. [19] applied explainable AI techniques such as Grad-CAM and LIME to improve interpretability, although standardized evaluation frameworks remain limited. Yuan et al. [20] proposed multi-scale CNN segmentation models for improved lesion boundary detection but reported sensitivity to noise and artifacts.Alternative architectures and deployment paradigms have also been investigated to enhance

accessibility and efficiency. Perez et al. [21] utilized ResNet-based classifiers without incorporating symptom-level correlations. Haenssle et al. [22] compared CNN systems with dermatologists, underscoring clinical trust and validation challenges. Vision Transformer architectures introduced by Dosovitskiy et al. [23] demonstrated strong global feature modeling capability but required data-intensive training. Multimodal image–text fusion approaches [24] improved contextual understanding while increasing architectural complexity. Cloud-based AI dermatology platforms [25] improved scalability but introduced privacy and latency concerns.Recent developments increasingly focus on edge intelligence and preventive dermatological screening. Liu et al. [26] proposed quantized CNN-based edge AI frameworks to reduce inference latency with minimal accuracy degradation. Patel et al. [27] addressed disease severity prediction using CNN-based scoring systems but did not incorporate explainability mechanisms. Teledermatology integration using AI-based models [28] improved accessibility but remained sensitive to image

quality variations. Hybrid CNN–random forest approaches [29] improved classification robustness, though feature fusion strategies were suboptimal. Preventive dermatology frameworks leveraging multimodal CNN and textual analysis
[30] emphasized the importance of large-scale clinical validation and real-world testing.Despite significant progress, key limitations persist across existing systems. Most approaches rely primarily on image-only analysis and lack structured integration of complementary textual or clinical information, thereby restricting diagnostic context. Additionally, high computational complexity, limited interpretability, and deployment constraints hinder widespread adoption in preventive and continuous dermatological monitoring. These challenges highlight the need for a unified, scalable, and multimodal framework that balances accuracy, efficiency, interpretability, and real-world usability. The proposed EpiSure system addresses these gaps by integrating dermatological images with contextual metadata within a robust multimodal AI architecture, enabling improved diagnostic reliability and practical deployment in diverse healthcare environments.

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