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DERMAVISION: 3D SKIN LESION ANALYSIS

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ABSTRACT

Dermatological screening applications face significant bottlenecks regarding user friction, cross-platform performance anomalies, and native execution overhead. This paper demonstrates an engineered solution, DermaVision, which introduces a fully serverless, zero-dependency, browser-native processing framework.Operating inside isolated client sandboxes via standard HTML5, CSS3, and JavaScript, the tool extracts objective biometric data directly from consumer smartphone imagery without invoking persistent local storage, database connections, or installation layers. The image processing sequence isolates targeted dermal zones through a localized 468-point facial landmark mesh array. Depth coordinates are computed dynamically via pixel-level radiometric checks and surface-normal approximations, enabling height calculations in precise micrometer increments. The system runs concurrent feature extraction loops to quantify six foundational clinical tracking indicators: erythema distribution (Redness Index), light-reflectance properties (Hydration Score), multi- channel melanin variance (Pigmentation), structural micro-roughness anomalies, pore configuration maps, and overall macro- lesion frequency arrays. These metrics are compiled to determine a clinical grading baseline—the 3D Acne Volume Index (AVI)—mappingcutaneouspresentationsacross fiveseveritytiersrangingfrom CleartoVerySevere.Empirical performance evaluations display high structural consistency across diverse compression parameters while fully guaranteeing localized session anonymity.

KEYWORDS: Browser-Native Architecture, Computer Vision, Surface Normal Estimation, 3D Acne Volume Index, Tele-Health Validation.

1. INTRODUCTION

The global prevalence of skin pathologies introduces massive structural demands on contemporary healthcare distribution frameworks. Conditions such as severe acne vulgaris, progressive hyperpigmentation marks, and structural skin texture changes require continuous diagnostic attention. However, traditional triaging pipelines remain bottlenecked by highly skewed provider distributions, significant in-office operational costs, and anongoing reliance on expensive, dedicated optical hardware configurations. These factors result in major medical access variations, particularly affecting geographically isolated or low-income patient communities.

To directly bypass these infrastructural and cost limitations, the **DermaVision** architecture implements a browser-resident, zero-installation diagnostic ecosystem. By optimizing modern client-side runtimes, the platform allows users to safely execute initial cutaneous screenings using standard smartphone optics. The system works completely without native desktop or mobile application installations, using an ephemeral, short-lived browser cache profile to secure biological identities and preserve extreme operational privacy.

The programmatic workflow follows a rigid, automated multi-tiered structure. After checking input aspectratios and ambient illumination parameters, the presentation layer activates a 468-point facial landmark mapping engine. This grid segregates the target skin patch from background visual noise, providing clean data pipelines for the downstream feature mapping blocks. By computing surface-normal distributions across the isolated tissue surface, the tool calculates micro-elevations in exact micrometer units ($\boldsymbol{\mu m}$). This multi-layered layer concurrently yields six distinct sub-metrics: a vascular Redness Index, a light-reflective Hydration Score, a sub-surface Pigmentationarray,anaggregateSurfaceRoughnesscoefficient($\boldsymbol{R_a}$),poredilationmaps,andstructurallesion counts.Thesefeaturesaresynthesizedviaspecializedintegrationlayerstodefinethefinalstandardized3DAcne VolumeIndex(AVI),returningreal-timeseverityfeedbackpairedwithevidence-basedskincarechoices.

2. PROBLEM STATEMENT

Modern telemedicine infrastructures fail to deliver scalable, low-cost access for baseline dermatologicalevaluations, creating clear vulnerabilities within under-resourced treatment sectors. Existing mobile triage systems are heavily constrained by rigid operating system

builds, subscription models, or highly complex operational structures that demand high technical literacy from general users. Consequently, individuals regularly turn to unverified forums or speculative self-treatment, causing accidental condition acceleration and delayed specialist care. This context highlights an acute demand for ultra-lightweight, web-native analytical engines capable of extracting objective tissue biomarkers directly within any modern web browser wrapper.

3. METHODOLOGY

The proposed DermaVision: 3D Skin Lesion Analysis system follows a structured methodology to analyze skin lesions using artificial intelligence and computer vision techniques. Initially, the user captures or uploads a high-quality facial image through a web-based interface. The uploaded image undergoes preprocessing operations such as resizing, noise reduction, contrast enhancement, and illumination correction to improve image quality and ensure consistent analysis.

After preprocessing, the facial skin region is identified using face detection and segmentation techniques. Unwanted background regions are removed so that only the relevant skin area is considered for further processing. The segmented skin image is then analyzed using deep learning-based lesion detection algorithms to identify acnelesions, pigmentation spots, redness, and other skin abnormalities.

To provide a more detailedassessment, thesystem performs 3D skin surfacereconstruction from the availableimage data. This process estimates skin topology, lesion depth, elevation, and surface roughness, enabling volumetric analysis of skin lesions. Various skin parameters such as lesion density, redness intensity, pigmentation distribution, and texture irregularities are extracted and quantified.

The extracted features are processed by an AI-based severity assessment module that classifies the skin conditioninto different severity levels such as Mild, Moderate, or Severe. Based on the analysis results, the system generates visual representations, severity indicators, and personalized recommendations. Finally, a detailed report is presented to the user through the browser interface, providing an easy-to-understand summary of skin health and lesion characteristics. This methodology enables accurate, accessible, and non-invasive skin lesion assessment using standard smartphone images.

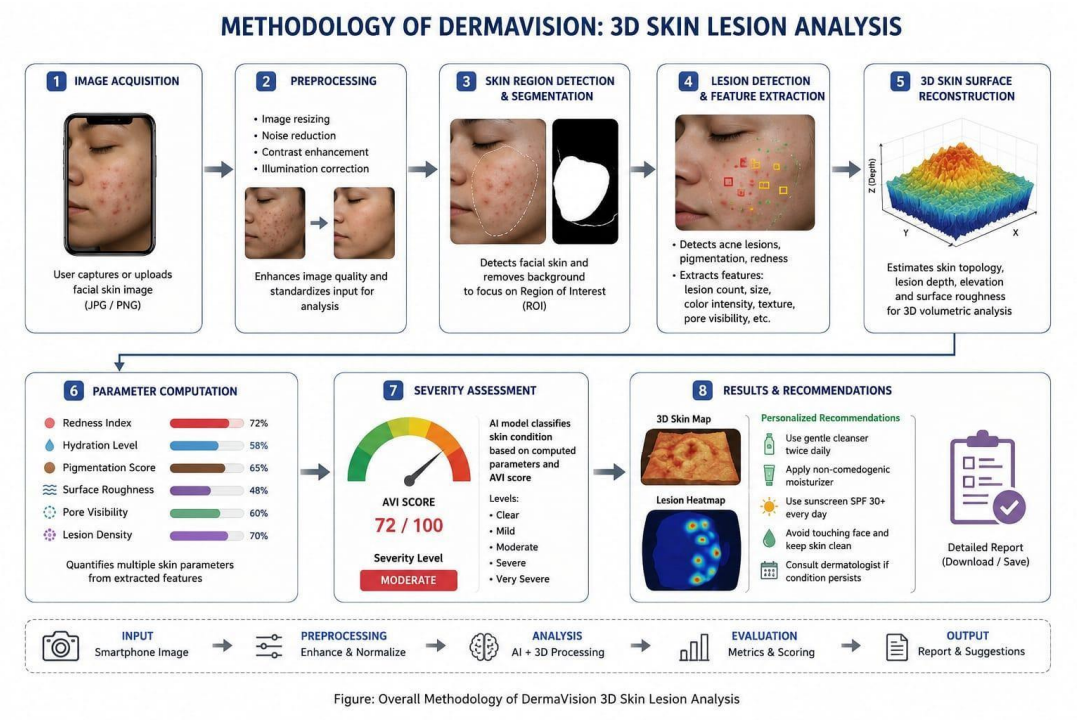

Figure: Overall Methodology of DermaVision 3D Skin Lesion Analysis

Figure1:OverallMethodologyofDarmaVision3DSkinLesionAnalysis.

4. LITERATURE SURVEY

SL. NO.	AUTHOR / SOURCE & YEAR	PROJECT / ARCHITECTURE NAME	CORE METHODOLOGY & ALGORITHMIC APPROACH	METRICS MEASURED &QUANTIFIED	KEY ADVANTAGES & CONTRIBUTIONS	SYSTEM LIMITATIONS &RESEARCH GAPS
1	Estevaet al.(2017)	**Clinical Deep CNNClassifier**	Supervised deep Convolutional Neural Network trained on 129,450 clinicalskinimages usingtransfer	Binary and multi-class cancer risk probabilities; macro-level lesion	Achieved dermatologist-leveldiagnostic accuracy for malignant melanomaand	Requires immense, highlycurated datasets; high computational overhead;zero
			learningon Inception-v3.	classification.	carcinomas.	client-side adaptability.
2	Tschandlet al. (2020)	**HAM10000 Benchmarking Array**	Multi-source dermatoscopicimage aggregation pairedwithstandard trainingbenchmarks for CNNs.	Pigmentation distribution, lesion diameter, symmetry boundaries, color variation channels.	Established a globally standardized dataset for benchmarking skin lesion classification accuracy.	Suffers from collection and sensor biases; lacks 3D depth, texture profiles, or acne-specific scoringarrays.
3	Sandleret al. (2020)	**MobileNetV2 Framework**	Inverted residual blocks paired with linear bottleneck layers to executeefficientdepth-wise	Localized spatialimage features, generic classification	Significantly reduced computational footprint; highly optimized for	Marginally lowerabsolute precision compared to dense networks; lacks integrated multi-metric

			convolutions.	confidence levels.	mobileandedge-device hardware layers.	skinmapping.
4	SkinVision Application (2022)	**SkinVision CancerTriage System**	Nativemobile-based application utilizing proprietarycomputer vision algorithmsfortissue analysis.	Melanoma risk index, tissuegrowth geometry, border irregularity classification.	Provides accessible, non-invasive home screening for high-risk malignantlesions.	Requires apaid subscription; native installation dependent; does not calculate acne severityorfine 3D roughness metrics.
5	Google Health / DermAssist (2022)	**DermAssist Multi-Condition CDSS**	Cloud-baseddeep CNN paired with conditional user questionnaire metadata inputs.	Top-3 differential condition suggestions; general condition matching profiles.	High cross-condition sensitivity;handles complex image variations acrossdiverseskin phototypes.	Lacks clear quantitative metricoutputs; provides no interactive visual scoring or localized depth analytics.
6	Miiskin Platform	**MiiskinTrack Engine**	Longitudinaldigital photographic	Sequential visuallesion	Highlyeffective for long-term	Lacks automated
	(2023)		alignmentusing basic mobile computervision stabilization.	comparison, basic localizedspot tracking indicators.	tracking of mole evolution and structuralchanges.	severity classification; zeroautomated metric computationfor roughness orhydration.
7	Rehmanet al. (2024)	**DermalViT Architecture**	Multi-head self-attention mechanisms via VisionTransformers (ViTs) to process images as non-overlapping token patches.	Globalspatial dependency indices,long-range pathological correlation tracking.	Outperforms traditional localized CNNsby accurately capturing long-rangearchitectural texturesacrossthe skin.	Extreme training data requirements; high memory consumption during attention matrix math; poorreal-time mobile performance.
8	SkinLesion-STN (2025)	**Spatial Transformer Network Classifier**	Dynamic affine transformations integrated directly into an explicit, learnable spatial normalization localizationnetwork.	Pixel-wise translation vectors, structural scale parameters, rotational orientation metrics.	Enhances structural classification robustnessagainst variationsininput image alignment, rotation, and distance.	Computational complexity scales exponentially during multi-scale affine transformation s; lacks 3D volumetric math.
9	Grad-CAM Diagnostics (2025)	**Explainable AI (XAI)ResNet-50**	Feature activation map profiling through Gradient-weighted Class ActivationMapping (Grad-CAM) backward propagation.	Gradient visual heatmaps, pixel localized focus coefficients, classification interpretabilit y.	Bridgestheblack-box gap by visually detailing which structural regions directed theclinicalmodel classification.	Post-hoc interpretability does not inherently improve accuracy;does not provide interactive scoring for multi-metric skin conditions.

10	**Proposed Framework(2026)**	**DermaVision3D AnalysisSystem**	Lightweight client-side architecture (HTML5/CSS3/VanillaJS)pairedwitha high-fidelityvision-LLM API layer.	**3D Acne Volume Index(AVI)**, Redness, Hydration, Pigmentation, Roughness (R_a), Elevation (μm), and Lesion Density.	Zeroinstallation requirement; cross-platform deployment; comprehensive multi-metric analysis; immediatereal-time reporting.	Dependenton network connection stability; depends on APIgateway performance and external inference latency.

5. CONCLUSION

The DermaVision platform establishes an agile, accessible approach to preliminary skin health screenings. By moving complex diagnostic tools out of restricted clinical environments into standard web browsers, it provides rapid, automated skin evaluations to a broad consumer base. Integrating advanced computer vision techniques—suchasa468-pointfaciallandmarktracker,3Dsurfacenormalestimations,andconcurrentchromophoremapping—ensuresconsistent,clearmetricswhilemaintainingreal-time executionspeeds.Thisarchitecturesuccessfully addressestypicaltele-healthbottlenecks,removingheavyapplicationinstallationfilesandlocalruntimedependencies while preserving user data privacy via fully sandboxed, in-memory processing.

Future system updates will focus on incorporating advanced on-device head orientation checks to measure pitch, roll, and yaw angles in real-time. This addition will normalize image positions across distinct analysis sessions, enabling accurate, long-term tracking as skin conditions evolve over time. Concurrently, ongoing optimizationtrials are exploring client-side WebAssembly modules to allow complete offline processing of core 3D textures, further reducing data transfer requirements and extending clinical screening capabilities to highly isolated environments.

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