DermaCon-IN: A Multi-concept Annotated Dermatological Image Dataset of Indian Skin Disorders for Clinical AI Research

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Abstract

Artificial intelligence is poised to augment dermatological care by enabling scalable image-based diagnostics. Yet, the development of robust and equitable models remains hindered by datasets that fail to capture the clinical and demographic complexity of real-world practice. This complexity stems from region-specific disease distributions, wide variation in skin tones, and the underrepresentation of outpatient scenarios from non-Western populations. We introduce DermaCon-IN, a prospectively curated dermatology dataset comprising 5,450 clinical images from 3,002 patients across outpatient clinics in South India. Each image is annotated by board-certified dermatologists with 245 distinct diagnoses, structured under a hierarchical, aetiology-based taxonomy adapted from Rook's classification. The dataset captures a wide spectrum of dermatologic conditions and tonal variation commonly seen in Indian outpatient care. We benchmark a range of architectures, including convolutional models (ResNet, DenseNet, EfficientNet), transformer-based models (ViT, MaxViT, Swin), and Concept Bottleneck Models to establish baseline performance and explore how anatomical and concept-level cues may be integrated. These results are intended to guide future efforts toward interpretable and clinically realistic models. DermaCon-IN provides a scalable and representative foundation for advancing dermatology AI in real-world settings.

1 Introduction

Skin diseases pose a significant global health challenge, affecting billions of individuals and ranking among the leading causes of disease burden. The Global Burden of Disease 2019 [39] study identified dermatological conditions as the *fourth* leading cause of nonfatal morbidity worldwide. Common ailments such as fungal infections, acne, scabies, and eczema impact millions globally [21], underscoring the urgent need for improved diagnostic tools and equitable access to care.

Artificial intelligence (AI) has emerged as a promising solution for enhancing dermatological diagnosis and triage, particularly in resource-constrained regions with limited access to dermatologists. However, a critical bottleneck remains: the lack of representative training data that adequately

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DermaCon-IN sample images					
Descriptors	Patch, White (Hypopigmentation)	Fissure, Hyperkeratotic plaques, Scale	Erythema, Plaque, Scale	Erythema, Wheal	Patch, Plaque, White (Hypopigmentation)
Body Parts	Upper Extremities Hands (Manus) Fingers (Digits)	Lower Extremities Soles (Plantar Region)	Head Cheeks	Trunk Abdomen, Thorax, Upper Extremities Shoulders	Head Scalp
Main Class	Pigmentary Disorders	Keratanisation Disorders	Infectious Disorders	Inflammatory Disorders	Inflammatory Disorders
Sub Class	Pigmentary Disorders	Keratanisation Disorders	Infectious-Fungal	Inflammatory (Other)	Eczema and Dermatitis
Disease Label	Vitiligo	Palmoplantar Keratoderma	Tinea Faciei	Urticaria	Seborrheic Dermatitis

Figure 1: Sample images from DermaCon-IN dataset with skin lesion descriptors, body parts, main class, sub class, and disease labels.

captures diversity in disease presentations and skin tones based on regional relevance [4]. Most AI models for dermatology to date have been developed and benchmarked using datasets predominantly sourced from North American, European, or Australasian populations [1, 26]. This geographic skew has introduced performance biases, especially for underrepresented groups such as individuals, patients presenting with diseases more prevalent outside Western contexts, and those with darker skin tones.

Recent work reveals the consequences of biased dermatology datasets [1, 28]. Public benchmarks focus on pigmented lesions and melanoma, mirroring Western priorities, while overlooking common conditions in tropical regions, like fungal infections, scabies, pigmentary, and nutritional disorders [37, 39, 21, 11, 20]. A "one-size-for-all" approach fails across populations, demanding region-specific resources. Under-representation of darker skin tones compounds this gap: [4] reports 30-40% accuracy drop on darker skin in DDI, while trained on Fitzpatrick17k's dataset (dominant lighter tones in the dataset). These biases lead to models that underperform on underrepresented phenotypes.

To address these limitations, we introduce a new dermatology image dataset curated from Indian outpatient clinics. To the best of our knowledge, it is the first densely annotated dataset centered around Indian skin phototype and is designed to improve diversity in both disease coverage and skin tone representation for dermatological AI research. It complements existing datasets by capturing the phenotypic and pathological landscape of a population historically underserved in global medical AI efforts. In addition, the dataset also aims to support explainable modeling by reflecting how dermatologists diagnose, through the combined use of anatomical location and visual descriptors. The Key contributions of this work are as follows:

- **South Asian Clinical and Phenotypic Representation.** DermaCon-IN developed in South Asia reflects regional disease patterns, such as the high prevalence of infectious etiologies (fungal, viral, parasitic) observed in tropical outpatient settings [42, 12, 35, 2, 19]. This contrasts with existing datasets dominated by inflammatory or neoplastic disorders common in Western contexts [45, 16]. The dataset also includes Fitzpatrick skin types IV–VI, which are typically underrepresented in existing resources [10], offering a path to reduce fairness gaps in clinically deployable AI models.

- **Multi-Concept Clinical Annotations.** Each image is annotated with two independent sets of clinically meaningful metadata: precise anatomical locations and lesion-level descriptors that capture surface and morphological features of skin lesions (seen in Figure 1). To the best of our knowledge, this is the first publicly available dataset to offer both annotation types at this scale and granularity, supporting structured supervision and interpretable modeling.

- **Clinically Aligned Hierarchical Labeling.** Disease labels are organized in a three-tier hierarchy: main diagnostic class, etiology-based subclass, and specific disease label. This structure is derived from Rook's *Textbook of Dermatology* (the clinical gold standard) [9] and adapted to Indian dermatology practice. It mirrors diagnostic workflows in real-world settings, enabling both coarse- and fine-grained modeling.

- **Benchmarking for Classification and Interpretability.** We provide baseline results for disease classification and for Concept Bottleneck Models (CBMs) [23] that leverage the concept annotations. These benchmarks demonstrate the dataset's relevance for both predictive accuracy and to evaluate whether models are learning medically meaningful concepts in alignment with expert reasoning.

2 Related Work

Table 1: Comparative Survey of existing Dermatology Datasets available for AI research [Columns: **A**: Neoplasm & Tumors Centric, **B**: Broad Skin Disease Spectrum, **C**: Dermoscopic Single Lesion Focus, **D**: Real-time Multi-lesion Multi-Focus, **E**: Body Part, **F**: Lesion Descriptor, **G**: Rook's classification labels]

Dataset	Disease Distribut.		Acquisit. Type		Dense Annotat.			Source of Images		Skin Tone	Classes	
	A	B	C	D	E	F	G	Web Scraped (Atlas)	Geographic Location	Present	#Images	Hierarchical #level[#count]
ISIC Archive [18]	✓	✗	✓	✗	✓	✗	✗	✗	Europe	✗	∼485,000	1[9]
HAM10000 [40]	✓	✗	✓	✗	✓	✗	✗	✗	Austria,Australia	✗	10,015	1 [7]
DERM12345 [46]	✓	✗	✓	✗	✗	✗	✗	✗	Türkiye	✗	12,345	3 [5,15,38]
BCN20000 [14]	✓	✗	✓	✗	✓	✗	✗	✗	Spain	✗	18,946	1 [8]
PH2 [27]	✓	✗	✓	✗	✗	✓	✗	✗	Portugal	✗	200	1 [3]
PAD-UFES-20 [29]	✓	✗	✗	✓	✓	✗	✗	✗	Brazil	✗	1,612	1 [6]
DDI [4]	✓	✗	✗	✗	✓	✗	✗	✗	USA	✓	656	1[78]
Derm7pt [22]	✓	✗	✓	✗	✗	✓	✗	✓	Italy	✗	1,011	2 [5, 20]
Fitzpatrick17k [10]	✗	✓	✗	✓	✗	✗	✗	✓	–	✓	16,577	3 [3,9,114]
SD-198 [36]	✗	✓	✗	✓	✗	✗	✗	✓	–	✗	6,584	1[198]
SkinCon [5]	✗	✓	✗	✓	✗	✓	✗	✓	–	✓	3,886	✗
PASSION [8]	✗	✓	✗	✓	✓	✗	✗	✗	Africa	✓	4,901	1[4]
SCIN [43]	✗	✓	✗	✓	✓	✗	✗	crowd-sourced	USA	✓	10,000+	1 [419]
DermaCon-IN	✗	✓	✗	✓	✓	✓	✓	✗	South India	✓	5,450	3 [8,19,254]

Neoplasm-Centric Benchmarks: Early dermatology AI models were trained on datasets focused on neoplasms and tumours, such as the ISIC [18], HAM10000 [40], DERM12345 [46], etc, as discussed in Table 1. These primarily contain dermoscopic images and omit common diseases like infectious and inflammatory disorders. Dermoscopic imaging focusing on a single lesion further abstracts clinical variability in lighting, context, and lesion complexity, limiting real-time applicability.

Atlas-Sourced Clinical Datasets: SD-198 [36] and Fitzpatrick17k [10] introduced clinical (non-dermoscopic) photographs to broaden the coverage of disease spectrum. However, both are derived from educational atlases (like DermNet), not clinical repositories, yielding limited annotations. Moreover, the Fitzpatrick17k [10] dataset excludes several prominent diseases, including Fungal and Viral infections, and has skewed tonal variation of over 75% belonging to Types I–III.

Fairness-Focused Collections: Datasets like DDI [4] and PASSION [8] emphasise tonal representation but trade off diagnostic breadth. DDI includes fewer than 80 disease labels, of which neoplastic or pigmentary offer a larger contribution. PASSION [30] has pediatric participants' images across only four conditions (eczema, fungal infections, scabies, impetigo), selected for regional prevalence. SCIN [43]dataset, on the other hand, introduces crowd-sourced images, expanding coverage to common non-neoplastic conditions but mirrors U.S. disease patterns [24], thus under-representing both high-burden infectious, pigmentary, etc, disorders seen in global contexts and darker skin tones.

Our Dataset in Context: In South Asia, outpatient dermatology is dominated by inflammatory, infectious, pigmentary, and appendageal diseases [42], yet remains underrepresented in existing datasets. We address this gap with a dataset of 5,450 high-resolution clinical images collected prospectively from 3,002 Indian patients. It covers the disease spectrum aligned with Indian and global burden data. Each image retains anatomical context and is annotated by board-certified dermatologists with standardised diagnosis, as well as Fitzpatrick and MST skin tone ratings, which align with patterns observed in the Indian context [32, 33, 15]. The distribution of which is shown in Figure 2. Unlike prior work such as SkinCon [5], which retrofitted a set of lesion descriptors onto existing datasets, we capture both lesion and anatomical concepts at source and leverage the full concept set for statistical validation and model benchmarking.

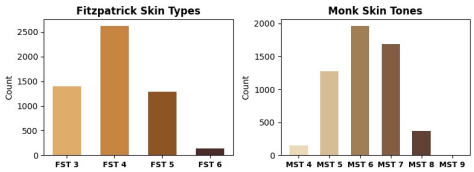

Figure 2: FST and MST distribution of skin tones of subjects in DermaCon-IN dataset

3 Data Collection Methodology

3.1 Clinical Setting and Data Sources

The DermaCon-IN dataset was developed via multi-institutional collaboration involving three tertiary-care hospitals and affiliated regional clinics across North Karnataka, South India. The cohort

represents a demographically and geographically diverse outpatient population from Karnataka, Maharashtra, Goa, and Andhra Pradesh. Data were collected between 2024 and 2025 under institutionally approved ethical protocols.

3.2 Image Acquisition Protocol

Image capture was designed to mirror real-world dermatology workflows, emphasizing both lesion detail and the broader anatomical region. Photographs were taken using high-resolution smartphone devices, viz, 108MP Android, 48MP iPhone Pro, and 12–36MP cameras, under ambient clinical lighting. Images include the affected body part with surrounding skin to preserve anatomical context and support spatial modeling. A standardized protocol guided acquisition across sites, allowing relevant variations in angle, distance, and lighting to reflect clinical realism, unlike prior datasets focused on dermoscopic or tightly cropped views.

3.3 Inclusion and Exclusion Criteria

Patients of all ages with clinically confirmed dermatologic conditions were included (with consent), contingent on diagnostic agreement by two board-certified dermatologists or follow-up validation. Only images meeting gradability standards and accompanied by complete metadata, including diagnosis, anatomical region, Fitzpatrick and Monk tone ratings, demographics, and diagnostic confidence, were retained. Exclusion criteria included poor image quality, visual obstructions (e.g., tattoos, accessories), metadata gaps, or ambiguous diagnoses, and patients unwilling to participate.

3.4 Annotation Process

The entire dataset was annotated by four board-certified Dermatologists with clinical experience of 11 years, 3 years, 3 years, and 1 year, respectively. The entire dataset was divided into four smaller subsets for labelling by these doctors based on the availability of the dermatologist. Labels followed a three-level disease taxonomy informed by Rook's Classification [9], which is considered a gold standard in Dermatology (Refer to Supplementary Sec. A). Annotations also included 47 lesion-level descriptors and 49 body part locations, along with patient metadata not linked to patients' privacy. Discrepancies were resolved via consensus or adjudication by a third expert.

3.5 Quality Control and Inter-Rater Agreement

To ensure consistency, 10–15% of each annotator's batch was randomly reviewed by another dermatologist. Inter-rater reliability, measured using Cohen's Kappa, achieved a score of 0.84 (Figure 3), aligning with accepted clinical annotation standards. Skin tone ratings were independently assigned by the set of trained experts, which was verified for consensus by the dermatologist. Anatomical site labels were validated using structured region maps.

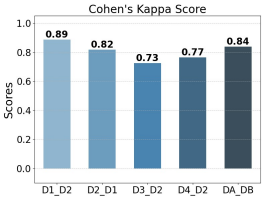

Figure 3: Cohen's Kappa scores for cross validation of annotations provided by 4 doctors (D1, D2, D3, D4)

3.6 Final Dataset Composition

The final composition contains $5{,}450$ high-resolution JPEG images across 8 top-level etiologic classes, 19 clinically meaningful subclasses, and 245 fine-grained disease labels. Each sample includes dense metadata: hierarchical disease labels, body parts, skin lesion descriptors, Fitzpatrick [7] and Monk skin tone [34] scores, diagnostic certainty, and image gradability. We consider 49 body parts and 47 lesion descriptors as concepts, which account for 96 unique concepts.

4 Dataset Overview and Statistics

Diagnostic structure and class granularity: DermaCon-IN is organized around an aetiologically informed, clinically validated taxonomy rooted in Rook's [9] classification and aligned with ICD-11 [44]. The dataset includes 8 high-level diagnostic categories ranging from Infectious to Neoplastic, including No Definite Diagnosis, reflecting the full spectrum of dermatological conditions prevalent in South Asian outpatient settings [42]. These main classes are further expanded into 19 subclasses to capture hybrid and co-occurring disease states. For example, subclass combinations such as Inflammatory + Infectious (Bacterial) reflect polymorphic real-world presentations of superimposed two diseases. Each top-level category is populated with sufficient training instances for stratified benchmarking; notably, high-burden groups like fungal infections and eczema dominate in volume, while rare but clinically significant categories, e.g., keratinisation disorders remain represented with enough density to enable few-shot generalisation. The Disease label reflects 245 distinct disease types, which follow a long-tailed distribution with a log-normal fit to leaf-node frequencies, yielding

an exponent of 1.8, as expected in real-world clinical settings. To better understand label diversity in the dataset, refer Figure 4. This visualization underscores the need for imbalance-aware learning strategies.

Lesion Descriptor annotations: The visual descriptors of skin lesions annotated in DermaCon-IN follow an established dermatological vocabulary commonly used by clinicians to describe skin lesions in line with extant clinical literature [3]. Inspired by frameworks [5] previously validated in dermatology AI literature, we consulted board-certified dermatologists to select clinically meaningful descriptors aligned with disease patterns frequently encountered in Indian outpatient settings. Rather than assigning fixed concepts per disease category, each image was independently annotated, reflecting the realistic variability in lesion appearance across patients, body regions, and skin types. Statistical analysis in Figure 5 of concept-disease correlations validated this flexible annotation strategy that supports concept-supervised learning approaches. Details of Descriptors utilized for annotation are provided in the Datasheet (Supplementary Material).

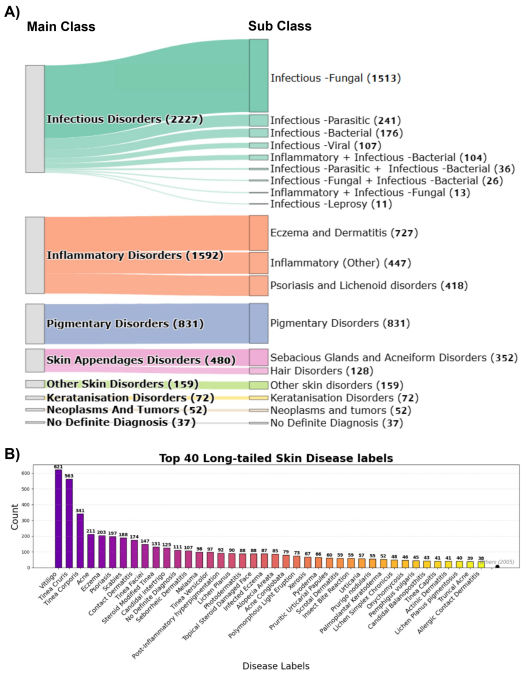

Figure 4: (A) Hierarchical structure of dermatological annotations (according to Rook's classification) showing main classes and their corresponding sub-classes with image counts (in bracket). (B) Distribution of the top 40 most frequent disease labels, illustrating the long-tailed nature of the dataset.

Anatomical Site annotations: We retain full views of affected anatomical regions wherever feasible. Partial cropping is applied in cases when identifiable facial features are present, in line with ethical guidelines to ensure patient privacy while preserving anatomical context reflecting how skin conditions are typically encountered in practice. This anatomical framing allows models to learn spatial priors: for instance, tinea capitis typically affects the scalp, while palmoplantar keratoderma appears on the palms and soles.

Such distributional cues are vital for accurate real-world diagnosis but are often lost in lesion-only images. Our dataset includes annotations for 49 distinct body sites, organised using both precise clinical terms and broader regional tags (e.g., trunk, extremities, scalp). A List of body parts annotated is provided in the the Datasheet (Supplementary Material).

Need for integration of Anatomical Context and Lesion Descriptors: Clinically, the same lesion type can indicate different diagnoses depending on its location; for example, a scaly plaque on the scalp might point to psoriasis, whereas a scaly plaque on the foot can suggest a fungal infection (tinea pedis). By jointly annotating lesion features (e.g., scales, plaques) and their anatomical context (e.g., scalp, foot), our dataset enables models to better reflect dermatologists' real-world diagnostic approach.

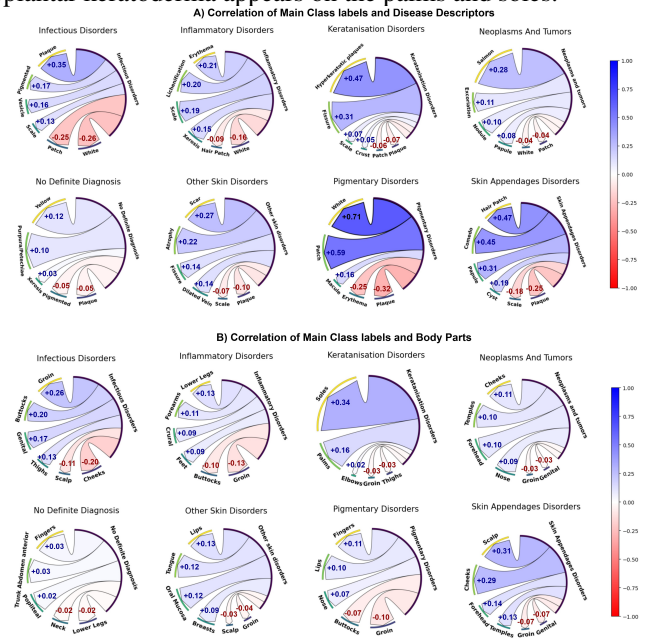

Figure 5: Chord diagrams of Pearson correlations (r) between eight disease classes and two concept types: **(A)** lesion descriptors and **(B)** body regions. Ribbon width represents within-class correlation strength, and colour encodes direction and magnitude (dark blue = positive; red = negative). Numbers on ribbons indicate r. Top-k positive and negative associations per class highlight distinctive clinical and anatomical patterns across disease groups.

Population structure and label density: The dataset reflects age and sex demographics typical of South Indian outpatient settings. The Dataset also adopts both Monk Skin Tone (MST) [34] and Fitzpatrick [7] scales, addressing the limitations of Fitzpatrick's UV-response bias. MST offers a perceptual alternative capturing wider tonal representation, especially for darker skin types, as the tonal scale has increased variation. The combined annotation aligns with Indian phenotypic distributions (MST 4–9, Fitzpatrick 3–4).

Statistical validation of concept and Anatomical coherence with Disease Labels: We examined Pearson correlation coefficients between (a) Disease descriptors and disease categories, and (b) anatomical body regions and disease categories, (refer Figure 5) to assess the biological plausibility and interpretability of our clinical annotations. Each chord diagram visualizes these relationships, where ribbon **width** indicates the strength of association between a concept and the class (within-class correlation) and ribbon **color** (dark blue $\rightarrow$ red) encodes the strength of correlation across classes (dark blue = strong positive; red = negative). Numeric labels on ribbons denote the actual correlation coefficients.

For instance, under *Pigmentary Disorders*, the descriptor *White* shows a moderately wide ribbon and dark-blue color ($r = +0.71$), reflecting a strong and distinctive association both within the class and relative to other classes. In contrast, *Hyperkeratotic plaques* under *Keratinization Disorders* display a wider but lighter-blue ribbon ($r = +0.47$), suggesting it is more class-specific but less distinctive across classes. Overall, the chord diagrams reveal statistically meaningful associations that align well with established dermatological knowledge. For instance, positive (high) correlations are observed between *erythema*, *vesicle*, and *scale* with inflammatory disorders, and between *hyperkeratotic plaques* and keratinisation disorders. Similarly, *white patches* and *pigmented lesions* show high positive associations with pigmentary and infectious disorders, respectively, underscoring the dermatologic specificity of the disease descriptors in general. Anatomical correlations further reinforce clinical fidelity. Keratinisation disorders predominantly localize to the *soles* and *palms*, consistent with plantar keratoderma patterns. Skin appendageal disorders, such as acne and seborrheic dermatitis, are strongly associated with sebaceous-rich zones like the *scalp* and *cheeks* [3, 31]. These findings validate the anatomical tropisms encoded in the dataset.

5 Challenges, Opportunities & Limitations

The dataset presents a range of challenges and opportunities that stem from the inherent complexity of real-world clinical data, offering both practical constraints and avenues for robust model development:

Resolution heterogeneity: Images were cropped post-acquisition to remove garments and background clutter where feasible, though incidental artifacts (e.g., jewelry) remain in some cases. The resulting variability in resolution, arising from diverse capture devices and aspect ratios, is a natural outcome, but advantageous. It reflects real-world conditions, where patients may crop or capture images themselves, and encourages model robustness to such variations. Image heights range from 296 to 4,608 pixels and widths from 346 to 4,608 pixels, with a mean resolution of 2,300x2,057 pixels. The average image area is 4.97M pixels ($\pm$3.01M), with an interquartile range of 2.62M–6.69M pixels (Figure 6), indicating consistently high-fidelity input for fine-grained modeling.

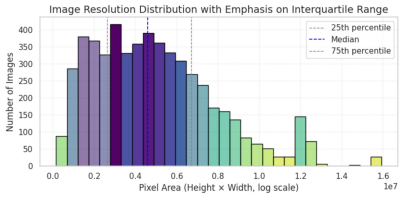

Figure 6: Resolution distribution of images in DermaCon-IN dataset

Hierarchical Labels and Clinical Distribution:

- **Class Imbalance:** Our hierarchical labelling across main and sub-classes reflects true outpatient frequencies, common conditions are well-represented, while others occur proportionally less. This mirrors real-world practice and enables models to learn from naturally occurring clinical distributions.
- **Long-tailed Disease Labels:** The dataset embraces the inherent long-tailed nature of dermatological diagnoses, where few diseases are prevalent and many are rare. This structure presents a valuable opportunity to train models that generalise across the full clinical spectrum, including rare disease categories.
- **Multi-disease co-occurrences:** A subset shows concurrent lesions from multiple disease types on the same anatomical site (e.g., *Inflammatory+Fungal*, *Fungal+Bacterial*). We

Table 2: Performance benchmarking of the proposed dataset on the 8-main class diagnosis classification task, conducted using both CNN- and ViT-based standard architectures. All metrics are averaged over 5 random seeds.

Model	Pre-trained	Accuracy	Balanced Acc.	Precision	Sensitivity	F1 Score
ResNet50 [13]	-	$47.45_{\pm 0.40}$	$23.93_{\pm 0.01}$	$46.59_{\pm 0.51}$	$47.44_{\pm 0.41}$	$46.43_{\pm 0.60}$
DenseNet121 [17]	-	$49.30_{\pm 0.30}$	$25.31_{\pm 0.01}$	$47.49_{\pm 0.86}$	$49.30_{\pm 0.29}$	$48.17_{\pm 0.74}$
ResNet50 [13]	ImageNet	$64.31_{\pm 0.22}$	$38.77_{\pm 1.40}$	$63.41_{\pm 0.29}$	$64.31_{\pm 0.23}$	$63.31_{\pm 0.25}$
DenseNet121 [17]	ImageNet	$65.20_{\pm 0.48}$	$37.31_{\pm 0.01}$	$64.62_{\pm 0.45}$	$65.20_{\pm 0.48}$	$64.37_{\pm 0.35}$
EffNet-B4 [38]	ImageNet	$64.28_{\pm 0.34}$	$35.58_{\pm 0.01}$	$63.53_{\pm 0.64}$	$64.27_{\pm 0.34}$	$63.38_{\pm 0.39}$
ViT-B/16-224 [6]	ImageNet	$64.09_{\pm 1.03}$	$34.56_{\pm 0.01}$	$62.59_{\pm 1.03}$	$62.88_{\pm 1.67}$	$62.98_{\pm 1.02}$
ViT-B/16-384 [6]	ImageNet	$66.95_{\pm 0.19}$	$35.78_{\pm 0.02}$	$65.39_{\pm 0.13}$	$66.95_{\pm 0.20}$	$65.78_{\pm 0.06}$
MaxViT-B/512 [41]	ImageNet	$66.92_{\pm 0.48}$	$36.07_{\pm 0.01}$	$66.30_{\pm 0.80}$	$66.92_{\pm 0.48}$	$65.90_{\pm 0.73}$
Swin-B/4W12-384 [25]	ImageNet	$\mathbf{70.41_{\pm 0.41}}$	$\mathbf{45.06_{\pm 0.02}}$	$\mathbf{69.83_{\pm 0.37}}$	$\mathbf{70.41_{\pm 0.42}}$	$\mathbf{69.69_{\pm 0.46}}$

Table 3: Performance comparison of model variants using the `Swin-B/4W12-384` backbone. The first two rows are baselines without a concept bottleneck (CB) layer, used for 8-main class (MC) and 19-subclass (SC) classification. The next four rows report CBMs trained with different concept sets: lesion descriptors (47), body parts (49), and both (96). The last merged rows present individual layer (SC & MC) performance of a Hierarchical CBM (Type 1 & 2) combining the CB layer with joint SC and MC classification as described in Fig 7. All metrics are results of end-to-end training and are averaged over 5 random seeds.

Classification head	Concepts	Accuracy	Precision	Sensitivity	F1 Score	Macro AUC
MC	-	$\mathbf{70.41_{\pm 0.41}}$	$\mathbf{69.83_{\pm 0.37}}$	$\mathbf{70.41_{\pm 0.42}}$	$\mathbf{69.69_{\pm 0.46}}$	$\mathbf{78.51_{\pm 0.59}}$
SC	-	$58.27_{\pm 0.22}$	$56.64_{\pm 0.45}$	$58.27_{\pm 0.22}$	$56.81_{\pm 0.43}$	$83.11_{\pm 2.55}$
(CBM-D) Concepts + MC	Descriptors	$68.57_{\pm 0.72}$	$67.63_{\pm 0.97}$	$68.55_{\pm 0.72}$	$67.69_{\pm 79.48}$	$85.18_{\pm 2.98}$
(CBM-B) Concepts + MC	Body parts	$68.38_{\pm 0.31}$	$67.69_{\pm 0.51}$	$68.31_{\pm 0.27}$	$67.90_{\pm 0.26}$	$84.96_{\pm 1.27}$
Concepts + MC	Descriptors & Body parts	$68.12_{\pm 0.43}$	$67.69_{\pm 0.71}$	$68.10_{\pm 0.48}$	$67.56_{\pm 0.48}$	$82.78_{\pm 2.70}$
(CBM-D) Concepts + SC	Descriptors	$56.42_{\pm 0.01}$	$55.72_{\pm 0.01}$	$56.51_{\pm 0.01}$	$55.63_{\pm 0.01}$	$80.16_{\pm 0.01}$
(CBM-B) Concepts + SC	Body parts	$55.88_{\pm 0.01}$	$55.47_{\pm 0.01}$	$55.90_{\pm 0.01}$	$54.87_{\pm 0.01}$	$78.94_{\pm 0.01}$
Concepts + SC	Descriptors & Body parts	$57.37_{\pm 0.01}$	$57.67_{\pm 0.01}$	$57.27_{\pm 0.01}$	$56.90_{\pm 0.01}$	$78.39_{\pm 0.02}$
(Type1) SC	Descriptors & Body parts	$53.98_{\pm 0.40}$	$56.12_{\pm 0.74}$	$53.98_{\pm 0.39}$	$54.49_{\pm 0.66}$	$76.13_{\pm 1.52}$
(Type1) MC	Descriptors & Body parts	$67.78_{\pm 0.47}$	$67.32_{\pm 0.67}$	$67.66_{\pm 0.48}$	$66.92_{\pm 0.37}$	$79.53_{\pm 0.62}$
(Type 2) SC	Descriptors & Body parts	$56.11_{\pm 0.67}$	$55.49_{\pm 0.0.62}$	$56.09_{\pm 0.9}$	$54.49_{\pm 0.66}$	$76.13_{\pm 1.52}$
(Type 2) MC	Descriptors & Body parts	$69.90_{\pm 0.20}$	$68.82_{\pm 0.36}$	$69.89_{\pm 0.19}$	$69.08_{\pm 0.31}$	$77.01_{\pm 2.24}$

represent these as dedicated subclasses to help models disentangle overlapping pathologies for the main-class label we follow dermatologists' treatment-priority logic, e.g., an infected eczema is assigned to the Infectious main class (not Inflammatory) because initial management targets the infection. Such cases, though less frequent, are observed in clinical settings, and our targeted misclassification analysis for these samples is provided in the Supplementary Sec. **B2**.

Instance-level concepts: These concepts describe what is visually observed in each image, such as scaling and erythema, and introduce two key characteristics that make DermaCon-IN a rich dataset for advancing clinical AI:

- **Class-agnostic semantics:** Descriptors (used as concepts) are shared across classes and are not rigidly tied to any single diagnostic category (e.g., *scaling* alone $\rightsquigarrow$ ichthyosis, whereas *scaling* + *erythema* $\rightsquigarrow$ psoriasis), with diagnostic meaning arising from their combinations. This invites the development of models capable of compositional and context-aware reasoning.
- **Long-tailed distribution:** The natural skew in concept frequencies mirrors real-world prevalence, where rare but critical findings coexist with common patterns. This creates opportunities to tackle challenges in multi-concept learning and rare concept detection, core problems in clinical AI.

Limitations. In accordance with ethical considerations, all images were anonymized by masking identifiable facial features, such as the eyes, and cropping facial regions where necessary. While essential for protecting patient identity, this may limit the model's ability to accurately learn or detect diseases that primarily manifest on the face.

6 Benchmarking with Models

6.1 Standard architectures

DermaCon-IN comprises high-resolution clinical photographs with multiple co-occurring lesions, varied anatomical regions, and hierarchically structured multi-label annotations. We selected archi-

tectures based on their complementary modelling strengths to benchmark model performance under these conditions. Convolutional neural networks such as ResNet50 [13], DenseNet121 [17], and EfficientNet (`EffNet-B4`) [38] are effective in capturing localised texture patterns and edge-level features, owing to their convolutional inductive biases and limited receptive fields. To complement this, we incorporated Vision Transformer (ViT) architectures [6], which leverage self-attention to relate spatially distant regions within an image. The ViT variants evaluated includes ViT-Base (`ViT-B/16-224` [6], `ViT-B/16-384`) [6], MaxViT-Base (`MaxViT-B/512`) [41], and Swin-Base (`Swin-B/4W12-384`) [25]. Among these, the Swin Transformer consistently achieved the best results for Main class prediction across evaluation metrics, demonstrating improved handling of both multi-class classification and class imbalance. Table 2 summarises the performance of all models considered. Swin Transformer's shifted window mechanism enables efficient modeling of non-contiguous regions, while its hierarchical representation captures both fine-grained lesion details and broader spatial patterns. These traits align closely with our dataset. We believe this alignment contributed to Swin's better performance.

Based on these observations, we adapted the `Swin-B/4W12-384` [25] variant of the Swin Transformer as the backbone for subsequent analysis and in concept bottleneck models (CBMs) [23] as shown in Table 3. The model was initialised with weights pretrained on ImageNet-22k and fine-tuned end-to-end on our dataset. Input images were resized and padded to 512×512 for further classification. We performed a stratified, subject-wise 80:20 split over Sub Class and reported all the results with the same split. We adapted weighted sampling strategies to handle class imbalance, and details of which are discussed in Supplementary Sec. B.

6.2 Concept Bottleneck Modeling for Interpretablity

Architecture. Given an input image x, the Swin-Transformer encoder E_θ yields a latent representation $z = E_\theta(x)$. A linear projection maps z to *concept logits* $c^\ell \in \mathbb{R}^{B+D}$, which are then passed through a sigmoid activation to obtain the interpretable *concept vector* $c = [c^{\text{bp}}, c^{\text{ld}}] = \sigma(c^\ell) \in [0,1]^{B+D}$, where c^{bp} denotes B **body-part** concepts and c^{ld} denotes D **lesion-descriptor** concepts. While both c and c^ℓ are used for interpretability and concept supervision, the downstream classifier f operates on the concept logits c^ℓ to produce task logits $y = f(c^\ell)$, predicting either a *Main-Class* (MC) or *Sub-Class* (SC) label. This architecture is presented in Figure 7(A).

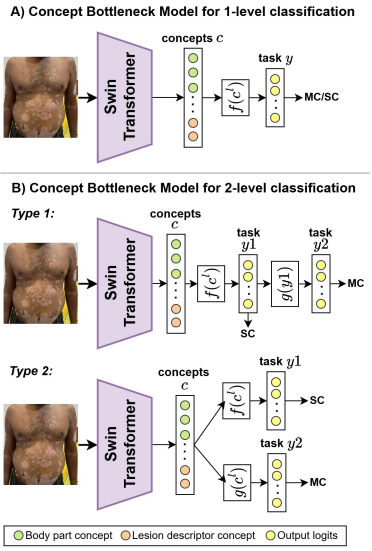

Figure 7: Architectural setup of Concept-bottleneck models for Main class (MC) and Sub class (SC) classification

Concept ablation and joint–stream effects. To quantify the contribution of each concept group, we trained two ablated models: **CBM-D**, which keeps only lesion-descriptor concepts c^{ld}, and **CBM-B**, which keeps only body-part concepts c^{bp}, both predicting MC labels. Each single–stream variant retained high accuracy (Table 2), demonstrating that the two concept families are independently learnable.

By contrast, the *full* CBM represents the true clinical diagnostic fidelity, in which both c^{bp} and c^{ld} co-exist in the bottleneck, achieved performance comparable to the individual concept streams, but revealed a systematic imbalance in activation: In many samples, only one concept group (typically descriptors) fired strongly, whereas the other (body parts) was under-activated (Fig. 8, bottom row). This led to a modest but consistent drop in overall accuracy, pointing to a *representational bottleneck* whereby competition for limited capacity biases the model toward a single semantic stream. These observations emphasize the need for improved multi-concept learning mechanisms that can balance several concept families simultaneously.

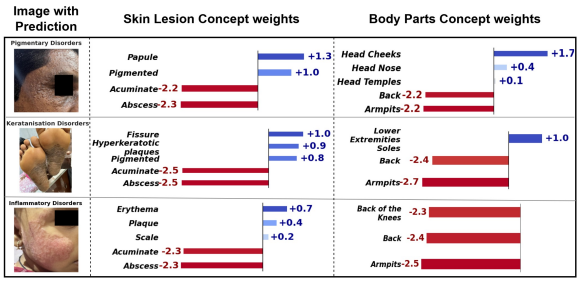

Figure 8: Bar plot of top and bottom-k contributing concepts (lesion descriptors and body parts) for the model's prediction. Contributions are shown as signed log-scaled weights derived from the CBM's intermediate logits.

Hierarchical CBMs. We explore two designs for joint SC–MC prediction (Figure 7(B)):

1. **Type 1 — cascade.** Concepts first predict sub-classes via $y1 = f(c)$. These logits are then mapped to the main classes through a second head $y2 = g(y1)$, ensuring taxonomy consistency by construction.
2. **Type 2 — parallel.** Both SC and MC are predicted from the shared concept vector through independent heads, $y1 = f(c)$ and $y2 = g(c)$, leveraging multi-task learning for implicit regularization.

Empirically, the *parallel* configuration surpassed the *cascade* alternative across all evaluation metrics (Table. 2), likely due to effective regularization and information sharing through the multi-task learning setup.

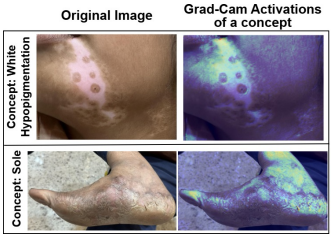

Figure 9: Examples of Grad-cam visualizations over Swin Transformer by choosing a specific concept with the best CBM model (Type-2).

Qualitative Analysis. To validate the spatial grounding of concepts, we employed Grad-CAM visualizations over Swin ViT on specific concept heads (Figure 9). For each selected concept (from both descriptor and body part categories), we backpropagated gradients from the concept prediction to the image space, producing activation heatmaps. These visualizations confirmed that the model's concept activations were often localized to semantically and anatomically appropriate regions, supporting the faithfulness of the learned representations.

To further assess whether the model's predictions are semantically grounded, we evaluate the alignment between its learned class-concept weights (MC branch of Type-2) and the statistical relevance (Pearson correlation, Section 4) of each concept to the class labels in the dataset (Figure 10). Alignment varies notably across diagnostic categories. *Pigmentary Disorders* and *Keratinisation Disorders* show strong Spearman correlations and statistically significant p-values ($p < 0.05$), suggesting that the model reliably prioritises clinically meaningful features for these classes. In contrast, *Neoplasms and Tumors* show weak or negative alignment, indicating reliance on non-semantic or latent cues, possibly due to low representation in the dataset. Whereas *No Definite Diagnosis* shows negative correlations as desired. Classes like *Skin Appendageal Disorders, etc.* exhibit partial alignment.

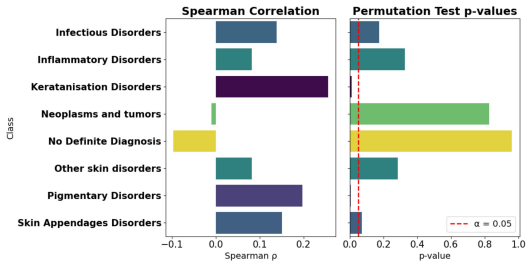

Figure 10: Class-wise assessment of alignment between the model's learned label weights over concepts and the dataset-derived correlation of concepts with class labels. The Spearman correlation measures the rank agreement between model-assigned concept importance and empirical concept–class correlations. Permutation test p-values (based on Pearson correlation) assess the statistical significance of this alignment.

Overall, these findings highlight that while the model is capable of learning semantically meaningful representations in some contexts, its reliance on concept supervision is uneven and class-dependent. This motivates future work in enforcing more robust concept–class alignment, particularly for clinically ambiguous or visually heterogeneous disease categories.

7 Conclusion and Future Directions.

DermaCon-IN captures real-world dermatological presentations from the South Indian population, offering concept-level annotations such as body parts and disease descriptors. It addresses gaps in skin tone diversity and regional disease patterns, serving both as a region-specific benchmark and a valuable addition to global dermatological datasets. By enabling evaluation beyond labels, it supports clinically grounded, interpretable learning, a step closer towards clinical deployment.

Targeted future work. Our findings point to several *method-driven* avenues for closing the identified gaps. These steps can help models to not only classify accurately but also reason in clinically meaningful ways. They are as follows:

- **Concept-weight normalisation:** Adding explicit regularisers that penalise disproportionate reliance on a single concept group, encouraging balanced gradient flow.
- **Hierarchy-consistent objectives:** coupling the SC and MC heads with cross-level consistency losses to discourage contradictory evidence pathways.

- **Curriculum and re-sampling strategies:** oversampling under-represented concept combinations (e.g. body-part signals within neoplasm classes) to equalize learning pressure across concept space.

Broader integration. Because DermaCon-IN offers strong coverage of South-Indian skin tones and disease spectra, its concept annotations complement existing global datasets. Merging these resources will enable training of larger, more broadly representative models, paving the way toward a unified *foundation-level* representation for dermatological imaging. Looking ahead, we will expand DermaCon-IN as versioned releases sourced from additional centers across India, thereby deepening geographic, phenotypic, and skin-tone coverage while preserving curation standards. In parallel, we plan to add pixel-level lesion masks for a subset of images, enabling segmentation and tighter alignment between concepts and spatial evidence. We hope this resource will move dermatology AI closer to responsible clinical use.

Ethical Clearance Statement: The dataset was collected in accordance with institutional ethical guidelines and has been approved by the Institute Ethics Committee of the Indian Institute of Technology Hyderabad under protocol number *IITH/IEC/2025/01/05*.

Implementation: The experiments were run on 4 GPUs of Nvidia-A6000, each of 42GB RAM. The dataset sizes around ~ 4 GB. The code used in this work is available at GitHub.

Availability and Licensing: The dataset can be downloaded at Harvard Dataverse. This work is licensed under CC BY-NC-SA 4.0. To view a copy of this license, visit creativecommons.org.

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