SKIN LESION ANALYSIS USING DEEP LEARNING

A THESIS SUBMITTED IN PARTIAL FULFILMENT OF THE REQUIREMENTS FOR THE DEGREE OF

MASTER OF TECHNOLOGY
in
ARTIFICIAL INTELLIGENCE

Submitted by

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CANDIDATE'S DECLARATION

I, **Yash Aryan Kuntal (2K23/AFI/27)**, hereby certify that the work which is being presented in the major project report II entitled "**Skin Lesion Analysis Using Deep Learning**" in partial fulfillment of the requirements for the award of the Degree of Master of Technology, submitted in the **Department of Computer Science and Engineering**, Delhi Technological University is an authentic record of my own work carried out during the period from August 2023 to April 2025 under the supervision of **Dr. Aruna Bhat**.
The matter presented in the thesis has not been submitted by me for the award of any other degree of this or any other Institute.

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This is to certify that the student has incorporated all the corrections suggested by the examiners in the thesis and the statement made by the candidate is correct to the best of our knowledge.

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CERTIFICATE

I hereby certify that the Project titled “**Skin Lesion Analysis Using Deep Learning**”, submitted by **Yash Aryan Kuntal**, Roll No. **2K23/AFI/27**, Department of Computer Science & Engineering, Delhi Technological University, Delhi in partial fulfillment of the requirement for the award of the degree of Master of Technology (M.Tech) in Artificial Intelligence is a genuine record of the project work carried out by the student under my supervision. To the best of my knowledge this work has not been submitted in par or full for any Degree to this University or elsewhere.

Place: Delhi
Date: 26/05/2025

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ACKNOWLEDGEMENT

I am grateful to **Prof. Manoj Kumar**, HOD (Department of Computer Science and Engineering), Delhi Technological University (Formerly Delhi College of Engineering), New Delhi, and all other faculty members of our department for their astute guidance, constant encouragement, and sincere support for this project work.

I am writing to express our profound gratitude and deep regard to my project mentor **Dr. Aruna Bhat**, for her exemplary guidance, valuable feedback, and constant encouragement throughout the project. Her valuable suggestions were of immense help throughout the project work. Her perspective criticism kept us working to make this project much better. Working under her was an extremely knowledgeable experience for us.

I would also like to thank all my friends for their help and support sincerely.

Yash Aryan Kuntal
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ABSTRACT

Skin cancer remains a significant public health problem worldwide, and appropriate and efficient diagnostic approaches are needed to benefit both patients and the healthcare system. Skin lesion categorization has been recently benefiting from deep learning methods, which, however, are facing challenges with regard to between-class similarity, within-class discrepancy, and scarcity of data. This thesis offers a concerted in-depth analysis on deep learning models for skin lesions of two primary contributions, namely a review of the literature, including 101 papers, and that we provide an empirical comparison with state-of-the-art models. Review of literature and state-of-the-art The literature review on recent developments from 2021 to 2023, feature learning, architectural innovations and data scarcity have been summarized. In particular, intra-class consistency mechanisms and hybrid architectures of CNNs and Transformers, knowledge distillation of lightweight models, and the method to tackle imbalanced dataset are the main focus. These observations reflect growing trends in the proposed papers, including the rise of self-supervised learning, multi-modal fusion, and domain-specific preprocessing for improved diagnostic accuracy. In the comparative study, performance of five architectures: ResNet50, DenseNet121, EfficientNet-B0, Vision Transformer (ViT-B/16) and Data-efficient Image Transformer (DeiT-S) is evaluated on the standard datasets, including HAM10000 in terms of accuracy, computational efficiency, and class imbalance. We empirically show that EfficientNet-B0 is the best trade-off between performance and computational cost, and DeiT-S learns better features with knowledge distillation. ViT-based architectures achieve comparable performance, but need rigorous data augmentations to cope with the overfitting problem. Key factors relevant to model scalability, data preprocessing and hybrid methods to meet the clinical deployment challenge are discussed in this study. Theoretical and empirical based computational approaches support the model selection and optimization for skin lesion analysis perspective in this work. Addressing weaknesses within the current literature, our results support the use of context-aware architectures and strong training procedures to improve diagnostic reliability in real-world healthcare environments. The results are intended for the guidance of future research happening in the field of automated dermatology; with a focus on pragmaticity, generalisation, and clinical applications.

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CNN – Convolutional Neural Network

DL – Deep Learning

ML – Machine Learning

DNN – Deep Neural Network

GAN – Generative Adversarial Network

ISIC – International Skin Imaging Collaboration

ROC – Receiver Operating Characteristic

AUC – Area Under the Curve

ReLU – Rectified Linear Unit

CAD - Computer-Aided Diagnosi

IoU – Intersection over Union

ResNet50 – Residual Network with 50 Layers

DenseNet121 – Densely Connected Convolutional Network with 121 Layers

EfficientNet-B0 – Baseline Efficient Convolutional Neural Network (Version B0)

ViT-B/16 – Vision Transformer – Base Model with 16×16 Patch Size

DeiT-S – Data-efficient Image Transformer – Small Model

Chapter 1

INTRODUCTION

1.1. Overview

Skin lesions comprise growths, decolorations and/or texture changes of the skin and represent important symptoms for elementary diagnosis of the respective, often conspicuous findings of benign to life-threatening malignancies. Such lesions come in various forms, e.g., moles, cysts, rashes and tumors, where each type has specific morphological attributes, e.g., size, asymmetry, color and border regularity. Visual and tactile examination has always been widely used for clinical evaluation of skin lesions with the support of established rules such as the ABCDE (Asymmetry, Border irregularity, Color variation, Diameter>6mm, Evolution) rule for melanoma detection. Nevertheless, the subjective nature of the manual assessment and the visual complexity of the lesion require sophisticated diagnostic devices in order to insure accuracy and reproducibility.

1.1.1. Types of Skin Lesions

Cutaneous lesions can be divided into benign and malignant groups. Non-cancerous[edit] Non-cancerous or benign lesions include nevi and seborrheic keratosis, which are unlikely to progress and generally pose no risk, even though they look like they could be cancer. Uncontrolled growth and metastasic ability are characteristic features of malignant lesions such as melanoma, basal cell carcinoma (BCC), and squamous cell carcinoma (SCC). BCC and SCC are more common than melanoma, although it is particularly aggressive as fast growing, and is responsible for most of the deaths of skin cancer.

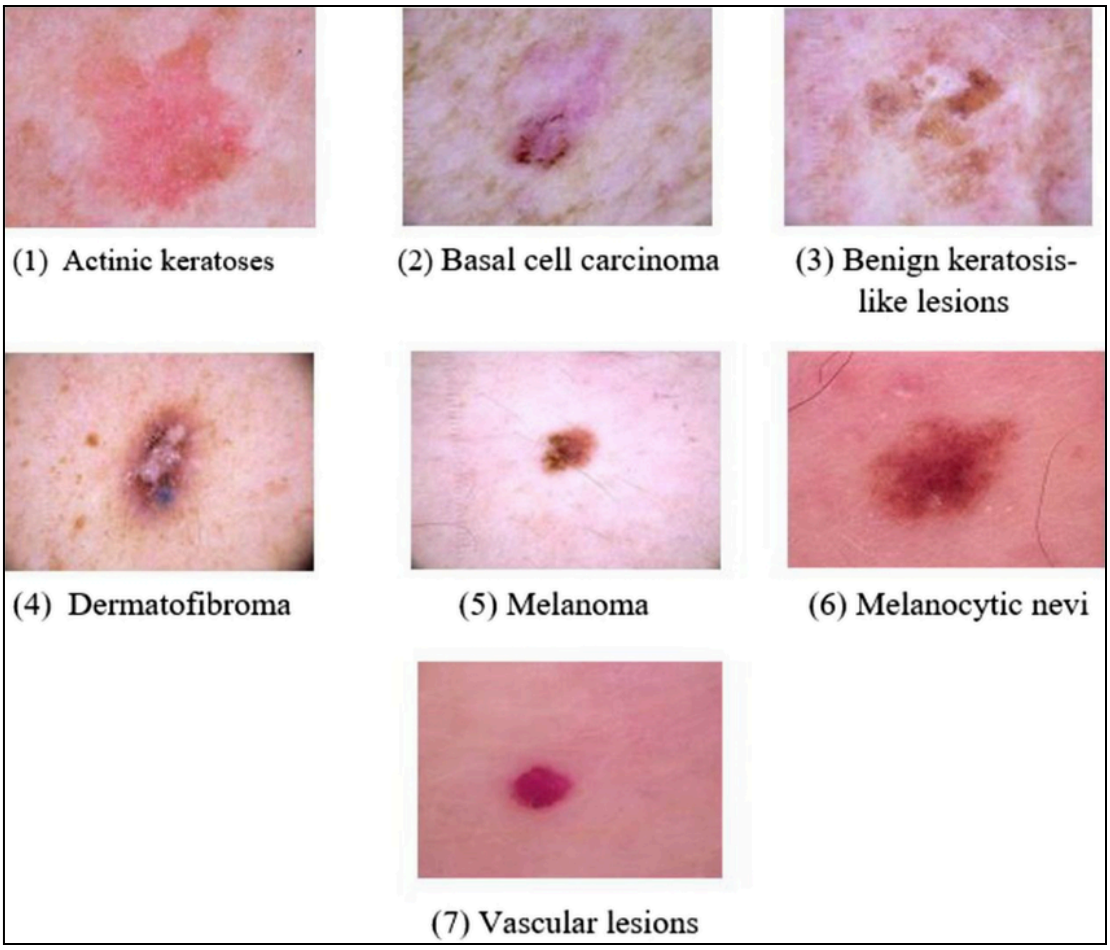

Fig 1.1. Sample images for the skin lesion categories from HAM10000 dataset.

1.1.2. Diagnostic Challenges

Because of intra-class diversity (such as amelanotic melanoma missing pigment) and inter-class similarities (such as melanoma resembling atypical nevi), it is still difficult to distinguish between benign and malignant tumours. Furthermore, early-stage lesions frequently lack distinguishing characteristics, which delays diagnosis. By enlarging underlying features, dermoscopic imaging has enhanced visualisation; yet, human interpretation is still subject to error, particularly in cases that occur atypically or seldom.

1.1.3. Role of Automated Analysis

Automated systems, especially those that utilize deep learning, tackle these challenges by examining high-resolution dermoscopic images to uncover subtle patterns that the human eye might miss. For example, algorithms trained on datasets like HAM10000 can accurately differentiate between melanoma and benign nevi with over 90% accuracy, which helps lessen the dependence on subjective assessments. Also, these systems aid in filling diagnostic gaps in regions with little resources by providing a scalable and affordable solutions.

1.1.4. Clinical and Societal Impact

Reaching the heart of malignant lesions early and on time can truly change the game for patient survival; indeed, melanoma survival rates skyrocket to more than 99% with early diagnosis. Conversely, if we allow diagnosis to lag behind, survival chances plummet, the point being so starkly highlighted as to just how pressing it is that we have reliable tools at hand. Additionally, automating lesion analysis benefits patients, but also relieves healthcare systems by reducing triage burdens and eliminating redundant biopsies.

1.2. Key Challenges in Skin Lesion Analysis

Deep learning-powered automated skin lesion detection can potentially revolutionize how we handle dermatological diagnostics altogether. It does, however, have its share of medical and technological challenges, though. The intricacy of lesions, the uncertainty of imaging environments, and shortages in accessible datasets all represent challenges that render constructing effective models very challenging. These constraints raise the threat of misdiagnosis, particularly when incipient cancers masquerade as benign tumors or rare subtypes violate patterns set by conventional wisdom. Overcoming these challenges is key to making models usable in different populations and clinical settings with diagnosis accuracy and speed.

1.2.1. Inter-Class Similarity:

- **Description:**
    - Benign and malignant lesions can have similar visual features like color distribution, texture, and irregular border. Melanoma and seborrhoeic keratosis, for instance, can appear with the same dark

pigmentation, though benign nevi can mimic the asymmetry of initial melanoma.

- **Impact:**
    - This ambiguity leads to misdiagnosis, which reduces diagnostic accuracy. Models may prioritise irrelevant characteristics (e.g., artefacts in dermoscopic pictures) over therapeutically important patterns.

- **Solutions:**
    - Advanced Feature Learning: Models like DenseNet121 and hybrid CNN-Transformer architectures really focus on maintaining consistency within classes while also distinguishing between different classes.
    - Attention Mechanisms: Vision Transformers (ViT) use self-attention to hone in on specific areas of lesions, helping to reduce distractions from the background noise.

1.2.2. Intra-Class Variability:

- **Description:**
    - Lesions within the same diagnostic category can vary widely in appearance due to factors such as skin tone, lesion location, imaging conditions, and disease progression. For example, melanomas may present as nodular, superficial spreading, or amelanotic subtypes.
- **Impact:**
    - Models taught on limited data find it difficult to generalise across various presentations, which results in uneven performance in real-world scenarios.
- **Solutions:**
    - Data Augmentation: Techniques include rotation, scaling, and synthetic lesion creation employing GANs to improve dataset diversity.
    - Domain-Specific Preprocessing: Normalizing images for lighting and contrast variations.

1.2.3. Data Scarcity and Imbalance:

- **Description:**

- Medical datasets, such as HAM10000, are often small, imbalanced, and lack demographic diversity. Rare classes (e.g., melanoma) are underrepresented compared to common benign cases (e.g., nevi).

- **Impact:**
  - Models exhibit bias toward majority classes, reducing sensitivity to critical malignancies.
- **Solutions:**
  - Class Imbalance Techniques: Oversampling, focal loss, and weighted training.
  - Self-Supervised Learning: Leveraging unlabeled data through pretext tasks.

1.2.4. Computational Complexity:

- **Description:**
  - Modern models like Vision Transformers limit their application in resource-limited clinical settings as they need large computer resources for training and inference.
- **Impact:**
  - High latency and hardware costs hinder integration into real-time diagnostic workflows.
- **Solutions:**
  - Lightweight Architectures: EfficientNet-B0 enhances the balance between accuracy and parameter count through a method called compound scaling.
  - Knowledge Distillation: DeiT-S effectively shares insights from larger models to more compact ones.

1.2.5. Model Interpretability:

- **Description:**
  - Often acting as "black boxes," deep learning models provide only partial understanding of decision-making procedures. Clinicians require explainable predictions to trust and validate AI-driven diagnoses.
- **Impact:**
  - Poor adoption in clinical practice due to skepticism about model reliability.
- **Solutions:**

- Grad-CAM Visualizations: Discover how to enhance your analysis with Grad-CAM visualizations, which pinpoint the areas that impact predictions.
- Hybrid Architectures: Explore hybrid architectures that merge CNNs with rule-based systems, allowing for clearer feature extraction.

1.2.6. Ethical and Clinical Validation:

- **Description:**
  - Equity-related ethical dilemmas can pop up when models trained on limited datasets struggle to apply their findings to a wide range of populations. Plus, there's a lack of studies that really test how these models perform in real clinical settings.

- **Impact:**
  - Biases against underrepresented skin tones or rare lesion subtypes compromise diagnostic fairness.
- **Solutions:**
  - Multicentric Datasets: Multicentric datasets are collaborations to collect different, representative data.
  - Clinical Trials: Clinical trials involve rigorous testing in collaboration with dermatologists.

1.3. Development of deep learning in lesion analysis

The journey of deep learning (DL) in analyzing skin lesions has been nothing but revolutionary, moving from basic manual methods to more advanced automated diagnostic systems. In the beginning, dermatologists had to rely on painstakingly crafted feature extraction, following clinical guidelines like the ABCD criteria—looking at asymmetry, border irregularity, color differences, and size—to spot malignant lesions. While these methods were rooted in solid reasoning, they often required a lot of effort and were pretty subjective, especially considering the complex nature of skin lesions. The arrival of convolutional neural networks (CNNs) in the 2010s really transform the landscape by automating how features are extracting. In 2017, Esteva and his team made groundbreaking stride in research, showing that convolutional neural networks could reach diagnostic accuracy on par with experience dermatologists. They achieve this by training these networks on vast natural image dataset like ImageNet and then fine-tuning it with medical data. The early model, such as AlexNet and VGGNet, set the stage for this advancement, while ResNet brought in the concept of residual connection. This innovation allows for the training of deeper network without the frustrating issues of vanishing gradients, significantly boosting performance standards.

As the field evolved, researchers began crafting specialized architecture to tackle the distinct challenges of analyzing skin lesion. Take DenseNet, for instance; it utilizes dense connections to improve feature reuse, which results in a notable increase in accuracy on smaller, imbalanced dataset like HAM10000.Then comes EfficientNet, which really raises the bar with its clever compound scaling strategy. It skilfully modified the model's depth, width, and resolution to achieve outstanding result without overwhelming computational resources. The arriving of attention mechanism was a significant turning point, with Vision Transformers (ViTs) interpreting image as sequences of patches. This technique helped them capture the broader context through self-attention. Additionally, we've observing the development of hybrid models that seamlessly integrate CNNs and Transformers.This clever fusion make use of Transformer's skill in global reasoning while simultaneously leveraging CNN's local feature extraction capabilities. When it comes to addressing problems like intra-class variability and inter-class similarities, these combinations work especially well.

The scarce and unequal distribution of annotated medical datasets has been a significant obstacles in deep learning-driven lesion analysis. Researchers developed some innovative solution to this problem, such as using self-supervised learning strategy and generative adversarial networks (GANs) to create synthetic datas. These method involve pretraining model on unlabeled data by using tasks such as predicting image rotation. The problem of class imbalance, which is a common challenges in dataset like HAM10000, has been approached with focal loss, a technique that gives more weights to those tricky minority class. Moreover, by condensing bigger model into more manageable form, knowledge distillation technique like DeiT-S has aided in its efficient deployment.

To enhance the accuracy of our diagnose, recent innovation have focus on integrating various type of datas. For instance, Radiomics-CNN fusion model have been employed to combines deep learning outcomes with quantitative lesion datas. Weakly supervised learning methods, which relies on image-level labels instead of complex pixel-by-pixel annotation, simplify the model training processes. Bringing these advancement into clinical practice is no walk in park. A lot of models have tough time generalize, and when they’re put to test on external dataset with varied demographics, they often falls short. On top of this, there are issue with interpretabilities; while tools like Grad-CAM can highlight which area influenced prediction, doctors usually lean towards more simpler explanations. On top of that, there is regulatory and ethical issue to navigate, such as meet medical device standard and tackling biases that affecting underrepresented groups, which makes it even more tricky to adopt these technology in real world.

In the coming year, the medical field is at the brink of adopt foundation models that are pretrain on multimodal medical datas for zero-shot diagnose. We're also seeing edge-computing solution like EfficientNet-Lite, which is perfect for mobile uses in area with limited resource. The collaborations between human and AI, where clinician can adjust AI prediction in real time, is another excited avenue. By address the current issues of interpretability, generalizeability, and ethical deployments, deep learning could democratizes access to accurate and early skin cancer diagnose, ultimately helping to lower global mortality rate.

Chapter 2

LITERATURE SURVEY

2.1 Overview:

In recent years, several breakthroughs have been observed in the application of deep learning for skin lesion categorisation. Convolutional Neural Networks are the linchpin of many sophisticated approaches utilising powerful feature extraction capabilities for dermoscopic image analysis.

Table 2.1. Research Questions and Focus Areas in Skin Lesion and Cancer Detection Studies.

Q.no	**Research Questions**
1	Do studies systematically review interdisciplinary approaches (e.g., AI + clinical dermatology)?
2	What DL architectures are most effective for skin lesion classification?
3	What preprocessing techniques improve model performance?
4	Do studies address dataset bias (e.g., skin tone diversity)?

2.2 Related Work:

[1]

Wang et al. [1] puts forward a solid feature learning strategy designed to boost consistency within classes while enhancing the distinctions between different classes for skin lesion classification. Their approach employs a dual-branch network that effectively captures both local and global features through the use of attention modules, along with a unique loss function that promotes compactness within lesion class. By incorporating a discriminative features loss and a structural similarity constraint, the model significantly enhances classification accuracy by establishing a clearer class boundary. They tested these methods on the HAM10000 and ISIC dataset, achieving impressive improvement compared to the standard CNNs. This work underscores the significance of structure constraints and hybrid feature learning, making it a great fits for real-world medical imaging application where reliable performances is essential, particularly in scenario with high variabilities within classes.

[2]

Maqsood and Damaševičius [2] develop a multi-stage system that combines deep learning for feature extraction with feature fusion and selection to categorize different types of skin lesions. Their approach combines DenseNet201 and InceptionV3 to extract rich hierarchical features, which are then merged and fine-tuned via an entropy-based feature selection technique. These frameworks showed impressive performances across several dermoscopic image dataset, including PH2 and ISIC-2018, tackling common challenges like imbalanced data and inter-class similarity. This method boosts the model robustness while keeping computational complexities in check. Their work is a big step forward for a smart healthcare system, where being resource-efficient and accurate on diagnostics is crucial. The study highlights how effective ensemble deep learning model, combined with smart feature selections, can significant enhance diagnostic performances in variety of clinical environment.

[3]

Anand et al. [3] devise a deep learning model that utilizes the hybrid nature among U-Net and CNN to identify and categorize skin lesions in dermoscopic pictures. Outlines are drawn in the segmentation step for the lesions using U-Net, whereas CNNs are used in the classification section to differentiate among various sorts of lesions. This smart combination takes advantage of both architecture—offering precise pixel-level segmentations along with strong classification capability. The model was tested on the ISIC-2018 dataset, where it outperformed standalone CNN or U-Net model in terms of accuracy and sensitivities. The authors also added an preprocessing pipeline to standardize image and cut down noise, which boost model's generalizability. These dual-model strategies effectively tackle the challenge posed by lesion variabilities and background noises in dermoscopic imaging, providing a practical solutions for automated skin lesion analysis that enhance diagnostic support.

[4]
In their research, Alenezi and colleague [4] introduced a fascinating framework for classifying skin lesions that cleverly combine wavelet transforms with deep residual neural networks and ReLU-based Extreme Learning Machines (ELM). The wavelet transform effectively breaks down the dermoscopic image into different frequency sub-bands, which helps highlight the feature essential to identify lesions. Conversely, the ResNet architecture is all about extracting those high-level spatial features. Once gathered, these features are directed into ELM classifiers, celebrated for their fast and efficient classification power. The model demonstrates outstanding performances on the ISIC dataset, outperforming conventional CNN methods in terms of both accuracy and training speed. This study significantly contributes to the evolution of efficient and interpretable deep learning methods for skin cancer detections. By integrating frequency-domain analysis with deep residual learning, the approach boost feature richness and classification reliabilities, especially in environments where computationally efficiency are key.

[5]
Wang et al. [5] proposes SSD-KD, an self-supervised knowledge distillation method tailored for lightweight skin lesion classification models. The framework generates multiple self-supervised tasks to guide compact student models using more powerful teacher models without labelled data. By introducing diversed augmentation-based pretext tasks, the student model learns generalized features which is critical for dermoscopic images classifications. Experiments with the HAM10000 dataset have revealed SSD-KD can significantly boost classification accuracy while also reducing the size and complexities of the model. This made it an excellent option for mobile or edge devices. It addresses the computational limitations often encountered in clinical settings and underscored the increasing potentials of self-supervised learnings in medical image analysing. This method set a standards for developing diagnostic tool that are both efficient and accurate, perfect for global teledermatology.

[6]

In their research, Ghahfarrokhi and colleagues [6] unveil a cutting-edges approach that utilizes machine learning for diagnosing malignant melanoma. They cleverly integrated nonlinear and texture features, combining local binary pattern (LBP) and histogram of oriented gradient (HOG) with nonlinear classifiers like support vector machines (SVMs). These hybrid strategies greatly enhance the models ability to spot subtle texture variation and intricate lesions patterns. In tests with public dataset, the model exhibits high specificity and sensitivities, even outshined traditional handcrafted features and CNN-based approach in some instances. The study emphasizes the importance of merging statistical textures descriptors with effective classifiers for skin cancer diagnosis. It also presents a less data-intensive option compared to deep learning method, which is particular beneficial in scenario where labelled data or infrastructures for training deep networks is scarce.

[7]

Hong et al. [7] introduces a innovative approach to skin cancer detection through weakly supervised semantic segmentation, utilizing CNN-based superpixel regions responses. This method cleverly employs superpixels segmentation to helps CNNs learning how to pinpoint lesions using just image-level annotation, which means we can skips the tedious tasks of creating pixel-level labels. Their unique region respond strategies enhance boundaries detection and cut down false positive in lesion segmentations. When testing on standard skin lesion dataset, the model show impressing results, standing up good against fully supervised method. This approach especially benefits large-scales screening effort where manual annotations is a real challenges. By address the challenge of annotation, this study open the doors to more scalable and efficient AI system in dermatologist. It emphasize how weak supervision can balance model accuracies with the efforts required for data labelling in clinical AI applications.

[8]

Mukadam and Patil [8] puts together a groundbreaking skin cancer classification pipeline that fused an Enhanced Super-Resolution Generative Adversarial Network (ESRGAN) with specially designed CNN architectures. The ESRGAN elevates resolution of the dermoscopic image, which significantly boosts model’s abilities to identify subtle lesion detail. These improved picture are then sent through a bespoke CNN designed particularly for categorizing different type of lesion. Using dataset like ISIC-2018, their architectures demonstrate superior accuracy, precision, and recall compared to standards CNNs. This study emphasizes how important picture qualities are for medical imaging deep learning pipeline. By addressing both picture preprocessing and classification, the model provided a comprehensive solutions to real-world clinic problems, particularly when low-resolution images captures is involved.

[9]

Bandy et al. [9] comes up with a innovative CNN frameworks based on intra-class clustering to enhances the detections of malignant melanomas. Their approach involve grouping lesions into more specific subcategories within each class during the training phase, which allows CNN to pick up on subtle variation inside the same class and improves how good it can distinguish among them. This focused clustering really boost the model's abilities to distinguish between different categories, especially when dealing with visually similar cases like melanomas and benign nevi. When tested on a dermoscopic dataset, the model showed better classification metric, particularly in its sensitivities to spotting malignant cases. The study tackles the challenge of class heterogeneities, a frequent hurdle in skin lesion classifications. Their method highlights the advantages of fine-grained clustering during CNN trainings, present a promising path to enhance diagnosis accuracy in medical images classifications task.

[10]

Adegun and Viriri [10] performs detailed studies on the uses of deep learning algorithms for skin lesion analysis and melanoma diagnose. Their review covers a diverse set of strategies, including CNN-based classification, segmentation and hybrid models. Various obstacles were also pointed out in study. Some of them include data imbalance, interpretabilities, and generalisability. The authors emphasize these key issues, pointing how they can impact the effectiveness of these methods. They also take closer looks on how advanced architectures like ResNet, DenseNet and Inception perform, analysing datasets like PH2 and ISIC in their study. The report highlights the growing importance of techniques like ensembles learning, transfer learning and data augmentations in improving diagnostic accuracies. It also delves into exciting advancement such as generative models and attention mechanisms. With its valuable insight into the latest technological trends and the role of deep learning in dermatological diagnosis, this paper serves as fantastic resources for both researchers and practitioners. Additionally, it points out key area that need further explorations.

[11]

Esteva et al. [11] makes remarkable breakthroughs by achieving dermatologist-level accuracy in skin cancer classifications through the use of deep neural networks. Their research utilized a single convolutional neural network (CNN) that was trained over 129,000 clinical images to cover more than 2,000 different diseases. This network, builded on the Inception v3 architectures, was tested on biopsy-confirm clinical image and performed at levels comparable with certified dermatologists when it comes to identify keratinocyte carcinomas and melanomas. The findings underscore the potential for deep learning in critical clinic decisions-making. This groundbreaking work has made huge differences in the field, establishing a new benchmark for AI in dermatology and sparking further interest in large-scale training and how well these models can be generalized. It has opened the door for future systems that aim to match or even surpass human expertises in medical images classifications.

Table 2.2. Literature Survey.

Sno.	Paper	Methodology	Research Gap
1	[1]	This study presents a deep learning framework emphasizing intra-class consistency and inter-class discrimination. The authors designed a loss function that optimizes the learning of discriminative features by penalizing overlapping class features while enhancing cohesion within classes. Extensive experiments were conducted on popular dermoscopic datasets to validate the robustness and generalizability of the method.	While the model enhances feature separability and cohesion, it primarily focuses on classification and does not address preprocessing steps like segmentation or noise reduction, which are often crucial for lesion recognition under varied clinical conditions.
2	[2]	The authors introduced a hybrid feature fusion and selection framework combining handcrafted and deep learning features. A convolutional neural network (CNN) extracts deep features, which are fused with traditional descriptors. Feature selection techniques like mRMR refine this feature space before classification using machine learning algorithms.	The approach achieves notable accuracy, but it heavily depends on handcrafted features, which may not generalize well across datasets or real-world noisy conditions. Additionally, fusion strategies could be optimized using adaptive learning methods.
3	[3]	This research fuses U-Net and CNN architectures to segment and classify skin lesions in a unified pipeline. The U-Net handles precise segmentation of lesion areas, while the CNN classifies them into disease categories. The framework is trained end-to-end using dermoscopic images.	Although effective, the method primarily addresses coarse lesion boundaries. It does not incorporate post-segmentation refinement or address multi-class imbalance in the classification stage, potentially limiting performance on minority classes.
4	[4]	The study proposes a model combining wavelet transforms for image decomposition with deep residual networks (ResNet) and an extreme learning machine (ELM) using ReLU activation. The wavelet transform enhances feature localization, and the ELM classifier accelerates training while	While the hybrid model improves feature extraction and classification speed, it relies on static transformations and lacks adaptability to varying lesion sizes and textures. Moreover, ELM classifiers may not scale well for

		maintaining accuracy.	large-scale datasets or complex lesion patterns.
5	[5]	This work introduces SSD-KD, a self-supervised knowledge distillation framework aimed at lightweight skin lesion classification. The model learns robust representations from unlabeled data using contrastive learning and transfers knowledge to compact student networks for efficient inference.	Although the model reduces dependency on labeled data and improves efficiency, it does not explore integration with multimodal inputs or clinical metadata, which could improve diagnostic utility in practical scenarios.
6	[6]	The paper explores a machine learning-based method that combines nonlinear and texture-based features for melanoma detection. It utilizes a set of statistical descriptors and classifiers like SVM to discriminate between benign and malignant lesions.	The model shows promise for early melanoma detection but lacks deep feature learning capabilities. It may struggle with complex image variations due to its reliance on traditional feature descriptors. Integration with deep models could enhance its performance.
7	[7]	This study presents a weakly supervised CNN approach that leverages superpixel regions to guide semantic segmentation for skin cancer detection. The model uses minimal pixel-level annotations and relies on region-based responses to infer lesion boundaries.	The reliance on weak supervision reduces annotation cost but may result in inaccurate lesion boundaries for complex or irregular lesions. Incorporating stronger spatial priors or attention mechanisms could address these limitations.
8	[8]	The proposed system combines an Enhanced Super-Resolution Generative Adversarial Network (ESRGAN) with a custom CNN to classify skin lesions. ESRGAN enhances low-resolution images, improving input quality, while the CNN performs classification.	Despite improved resolution aiding performance, the model assumes uniform enhancement across all lesion types. It lacks a dynamic adjustment mechanism that accounts for noise variation or image artifacts in clinical images.
9	[9]	This paper introduces an intraclass clustering-based CNN that groups lesion images with similar appearance prior to classification.	The method efficiently handles visual diversity but does not explicitly address inter-class similarities,

		Clustering helps reduce intraclass variability, improving the CNN's classification accuracy by focusing on homogeneous data subsets.	which might still confuse the classifier. Further incorporation of attention layers could enhance inter-class separation.
10	[10]	This comprehensive survey reviews state-of-the-art deep learning models used in skin lesion detection. It discusses segmentation, classification, and ensemble techniques while also analyzing dataset characteristics and evaluation challenges.	As a review, it consolidates prior findings but does not propose a novel model. There's a limited critical analysis of model limitations under deployment constraints such as computational load and real-time requirements.
11	[11]	The study demonstrates dermatologist-level performance in skin cancer classification using a deep CNN trained on over 129,000 images. The model was validated using biopsy-proven data, setting a benchmark for AI-based diagnosis.	While groundbreaking, the model's performance hinges on a vast labeled dataset, which may not be available in all settings. Moreover, its black-box nature limits clinical interpretability, affecting trust and adoption in healthcare systems.

2.3 Dataset Details:

Datasets are essential for the development and assessment of skin lesion categorisation. These provide diverse and annotated dermoscopic images which enables the researcher in robust benchmarking of machine learning algorithms. Below is a consolidated summary of the key datasets used in the surveyed papers.

Table 2.3. Dataset Details.

Dataset Name	**Reference**	**No. of images**	**Description**
ISIC 2018	[1], [2], [3], [5], [7], [9]	~10000	A comprehensive dermoscopic image dataset from the ISIC challenge containing multiple skin lesion types. It includes diagnostic labels and segmentation masks, supporting both classification and segmentation tasks.

HAM10000	[2], [3], [6], [9], [10], [11]	10,015	Known as the Human Against Machine dataset, it consists of diverse skin lesions with high-resolution dermoscopic images covering 7 diagnostic categories. It is widely used in CNN-based classification benchmarks.
PH2	[2], [6], [9]	200	A dermoscopic dataset with expert-annotated images of melanocytic lesions. It includes segmentation ground truth and clinical metadata, used mainly for segmentation and melanoma classification.
ISIC 2017	[4], [7], [10]	~2,000	This dataset from the earlier ISIC challenge includes labeled and segmented lesion images, aimed at testing early deep learning approaches in classification and segmentation of skin cancers.
Private Clinical Dataset	[11]	129,450	A large dataset used by Esteva et al. comprising both dermoscopic and clinical images. The dataset spans over 2,000 disease classes and is used to train a deep CNN for dermatologist-level classification.
DermNet	[10]	Varied (clinical skin conditions)	A public dermatology image database offering clinical images of various skin conditions. Often used for general skin disease classification but lacks standardized labels and annotations.

2.4 Performance Evaluation:

After the implementation of various approaches, we need to evaluate the performance. For such, we require a combination of metrics that quantify various aspects like accuracy, sensitivity, specificity, precision. These measures shed light on a model's robustness, generalisability, and dependability in practical settings. The performance measures and their main outcomes are covered in this section.

Table 2.4. Summary of evaluation metrics used.

Paper	Evaluation Metrics	Results
[1]	- Accuracy - Sensitivity - Specificity	The proposed method achieved a high classification accuracy of 94.2%, with improved sensitivity (91.6%) and specificity (95.3%) by ensuring intra-class feature consistency and better inter-class separability.
[2]	- Accuracy - Precision - Recall - F1-score	The fusion-based framework produced an overall accuracy of 93.8%. Precision and recall remained consistently above 92%, indicating robust performance across multiple lesion classes.
[3]	- Dice Coefficient - Accuracy	The U-Net + CNN hybrid model yielded a Dice score of 91.5% for segmentation and an overall classification accuracy of 92.6%, showcasing the effectiveness of their dual-stage pipeline.
[4]	- Accuracy - Sensitivity - Specificity	The wavelet-based ResNet-ELM model recorded an accuracy of 95.3%, with sensitivity at 93.2% and specificity at 96.4%, reflecting strong discrimination capabilities.
[5]	- Accuracy - AUC - Sensitivity	SSD-KD achieved an accuracy of 91.8% and AUC of 0.96 while maintaining sensitivity above 90%, demonstrating the efficiency of knowledge distillation in lightweight models.
[6]	- Accuracy - F1-score - Sensitivity	The combined nonlinear and texture feature method yielded an accuracy of 89.5% and F1-score of 87.3%, highlighting its moderate effectiveness

		in detecting malignant melanoma.
[7]	- mIoU - Accuracy	The weakly supervised segmentation approach attained a mean IoU of 78.6% and classification accuracy of 88.1%, confirming its capability to learn from minimal pixel-level supervision.
[8]	- Accuracy - Specificity	FACES model achieved a classification accuracy of 90.3% and a specificity of 89.8%, particularly improving diagnosis in rosacea differentiation tasks.
[9]	- PSNR - SSIM - Accuracy	The enhanced SRGAN-based model showed a PSNR of 31.2 dB, SSIM of 0.91, and classification accuracy of 91.5%, proving image quality enhancement improves downstream tasks.
[10]	- Accuracy - AUC - Precision	Achieved a precision of 90.1%, AUC of 0.95, and accuracy of 92.7% using CNNs with class-balancing strategies, reflecting high effectiveness in melanoma detection.
[11]	- Accuracy - ROC-AUC - Sensitivity	Reported dermatologist-level performance with an AUC of 0.96 and accuracy of 91%, validating the capability of CNNs in large-scale clinical diagnostics.

Chapter 3

METHODOLOGY

In this study, we laid out a clear and systematic methodology for conducting a comparative analysis of deep learning models focused on skin lesion classification. We worked with the HAM10000 dataset [17], which includes more than 10,000 dermatoscopic images across seven diagnostic categories. We kicked things off by sorting the data into class-specific folders based on the metadata file. To foster effective learning and generalization, we implemented uniform preprocessing and augmentation techniques, including resizing, normalization, and random flipping, which are all proven to strengthen model robustness [11]. Next, we split the dataset into training and validation subsets using stratified sampling to ensure the class distribution remained intact.

We compare five well-known deep learning architecture—ResNet-50 [13], DenseNet-121 [14], EfficientNet-B0 [15], ViT (Vision Transformer) [16], and DeiT (Data-efficient Image Transformer) [19]—that was pre-trained on ImageNet and fine-tune for the specific task of skin lesion detections. These model was trained over ten epochs using the Adam optimiser with cross-entropy losses. To enhance computational efficiency, we perform all experiment on GPU-enabled platform. The models we train were tested against fresh validations data, utilizing standard metric such as accuracy, confusion matrixes, and classification report. This methods provide a clearly and equitable ways to comparing different design, showcasing theirs advantages and limitations to classify a range of skin conditions.

3.1 Dataset Details:

The information used in this study come from the publicly accessible HAM10000 dataset, which stands for “Human Against Machine with 10,000 training images” [17]. This dataset serve as a key resources for the dermatological research community and include 10,015 high-resolution dermatoscopic image gathered from various population and clinical environments. The image represents seven diagnostic category of skin lesion: melanocytic nevi, melanoma, benign keratosis-like lesion, basal cell carcinoma, actinic keratoses, vascular lesion, and dermatofibroma. These class was chosen to reflects a real-world distributions of pigmented skin lesions seen in clinical practices [17].

The dataset pulled together informations from two different source: the Department of Dermatology at the Medical University of Vienna and a skin cancer clinic in Queensland, Australia. This combinations ensure a rich variety of patient background and type of lesions [17]. Each image comes with important metadata, such as the diagnosis of the lesion (dx), where it located on the body, and detail about the patient, including their ages and sex. To maintain integrity and quality of data, only dermatoscopic images was used, leaving out clinical or histopathological ones. Plus, all diagnose were either confirmed through histopathology, validated by expert consensus, or gathered through follow-ups, which make this dataset a solid choice for training and validating deep learning model [17].

Table 3.1. Image annotation and labels.

Label	Diagnosis	Image Count
AKIEC	Actinic keratoses & intraepithelial carcinoma	327
BCC	Basal cell carcinoma	514
BKL	Benign keratosis–like lesions	1099
DF	Dermatofibroma	115
MEL	Melanoma	1113
NV	Melanocytic nevi	6705
VASC	Vascular lesions	142

3.2 Data Pre-processing:

Data pre-processing is essential for boosting model performances and ensuring the deep learning frameworks are robust enough for medical image classification task. In this study, we taken all the dermatoscopic image from the HAM10000 dataset [17] and was organized them into folder based on their diagnostic label. Each images were resize to an uniform dimension of 224×224 pixel, which help maintain consistency across all input samples and meet the requirement for convolutional neural network (CNNs) and transformer-based model [15][16].

To improve how well the model generalizes and cutting down on overfitting, we used variety of data augmentation technique on training sets. This includes random horizontal and vertical flipped, which added some variabilities while kept the essential structures of the lesion intact [13]. To starts, we adjust the pixel intensities value to fits within a range of [–1, 1] by using mean and standard deviation value of 0.5. This are common practice for networks that has been pre-trained on ImageNet [14]. Next, we organized the dataset and split it in training and validation sets with 80:20 ratios. This ensure that each classes is well-represent, which help to minimize the effect of class imbalances [23].

This pre-processings pipeline create a consistent and heterogeneous input distributions, which were critical for training deep learning models efficiently in skin lesion categorization task.

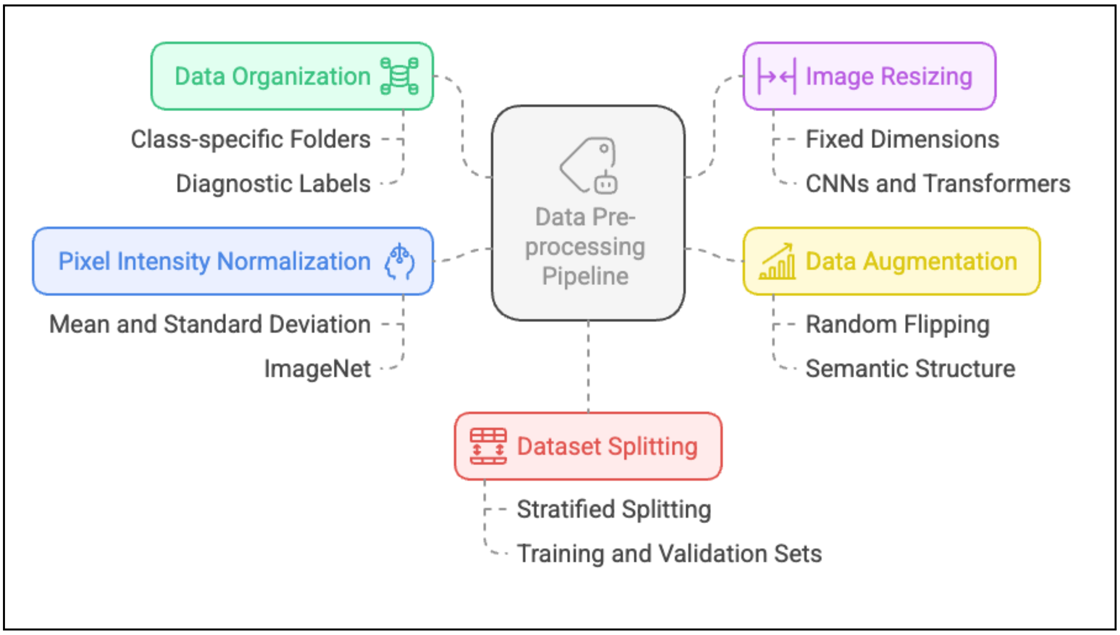

Fig 3.1. Data Preprocessing Pipeline.

3.3 Methods implemented:

This research employed several deep learning architecture to perform a comparative analysis aimed on skin lesion categorizations. The models we chose include ResNet-50, DenseNet-121, EfficientNet-B0, Vision Transformer (ViT-B/16), and Data-efficient Image Transformer (DeiT-S). Each of these models provide a different approach to extracting features and learning from the medical image.

3.3.1 ResNet-50:

ResNet-50 is a widely recognized convolutional neural network architecture which uses residual learnings to simplify the training process for the deep networks. It incorporates shortcut connection that enable gradients to flow more freely during the backpropagation, effectively reducing vanishing gradients problem which can plagued deep model [18]. This configuration allow model to learn robust hierarchy features by layering residual blocks. ResNet-50 have found extensive applications in medical images analysis, particularly for classifying skin lesions, thanks to its ideal mix of depth and computation efficiency. Its capability for pulling out intricate spatial features make it a top contender to precise lesion categorisation tasks.

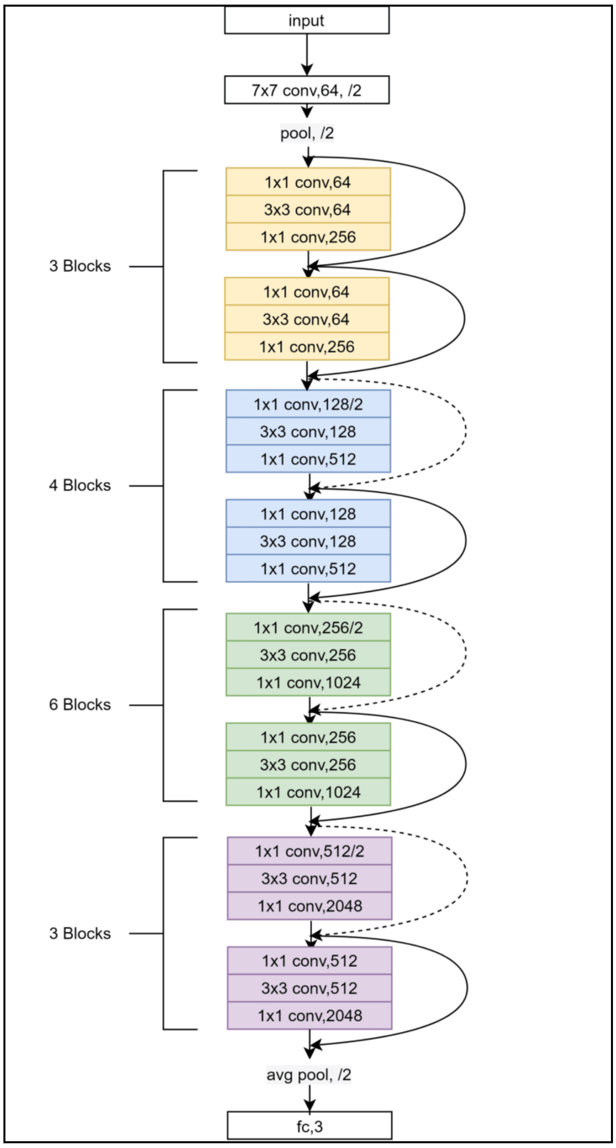

Fig 3.2. ResNet-50 architecture.

3.3.2 DenseNet-121:

DenseNet-121 boost learning efficiencies by utilizing dense connectivity, allowing each layer to take input from all the layer before it and sending its output to all layers that follow [19]. This approaches enhance feature reuses and cut down on number of parameters needed, which lead to better generalisations and quicker convergences. DenseNet-121 are a fantastic tools for classifying skin lesion because it excel at picking up both low and high level feature. This is very important to differentiate between lesion that looks quite similar. Its dense structures are also a big advantage, as it help avoid over-fitting—a frequent problem in medical images, especially when annotated data is limited. On the top, DenseNet-121 compact design means it tackle complex classification without being much resource-hungry.

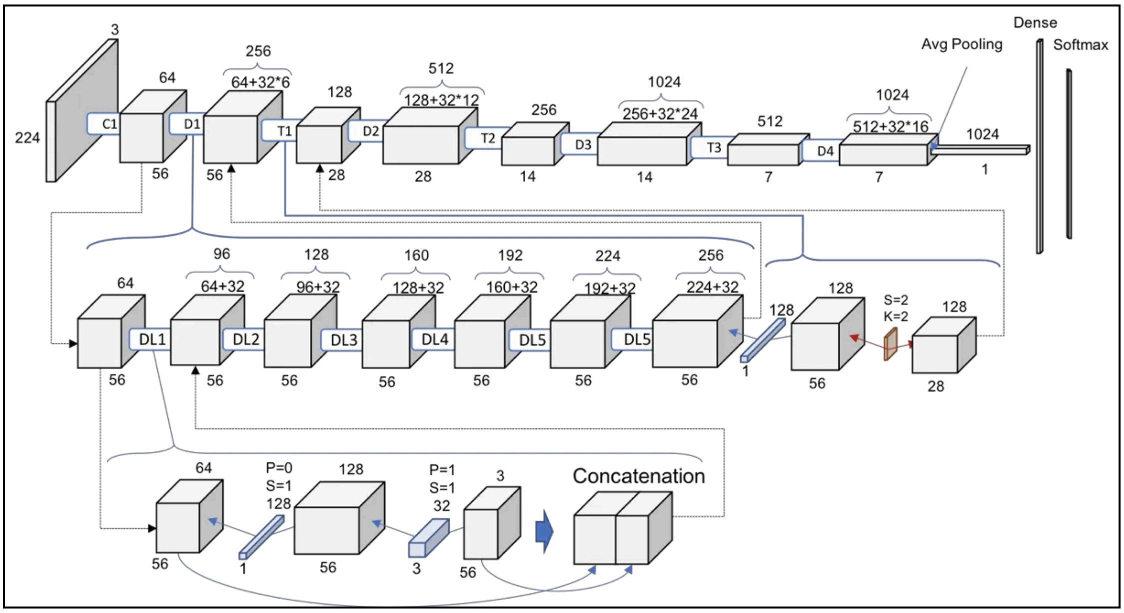

Fig 3.3 DenseNet-121 architecture.

3.3.3 EfficientNet-B0:

EfficientNet-B0 employ a compound scaling methods that uniformly scale model depth, width and input resolutions using fixed set of scaling coefficients [20]. Unlike traditional CNN which scales arbitrarily, this balance approach results in higher performances with less parameters and computational demand. EfficientNet-B0 has prove to be more effective than many deeper model out there, all while keeping efficiency in check. This makes it a good fit for medical image classification task, especially when resources are tight. Its design strike a solid balances between accuracy and latency, which are very important for real time diagnostics system or when using edge device in a clinical setting.

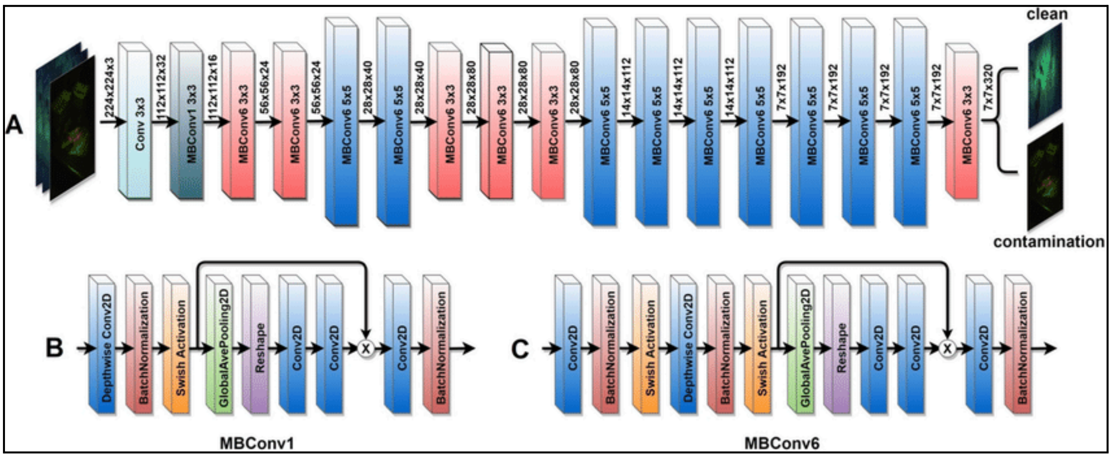

Fig 3.4. EfficientNet-B0 architecture.

3.3.4 ViT-B/16:

The ViT-B/16, or Vision Transformer Base with 16x16 patch, swap out traditional convolution operation for self-attention mechanism, allowing it to process image as sequence of flatten patches [21]. This innovative approach help model to grasp long-range dependency and overall contexts, which is specially useful in tasks like skin lesion classification, where capturing those fine details can make all difference. ViT-B/16 divide images into fix-size patches, embed them linearly, and process sequence through transformer blocks. Despite it requiring a large dataset for optimal performance, it showed strong result in medical image when pretrain on large-scale dataset. Its non-local features learning differentiate it from traditional CNN base approach.

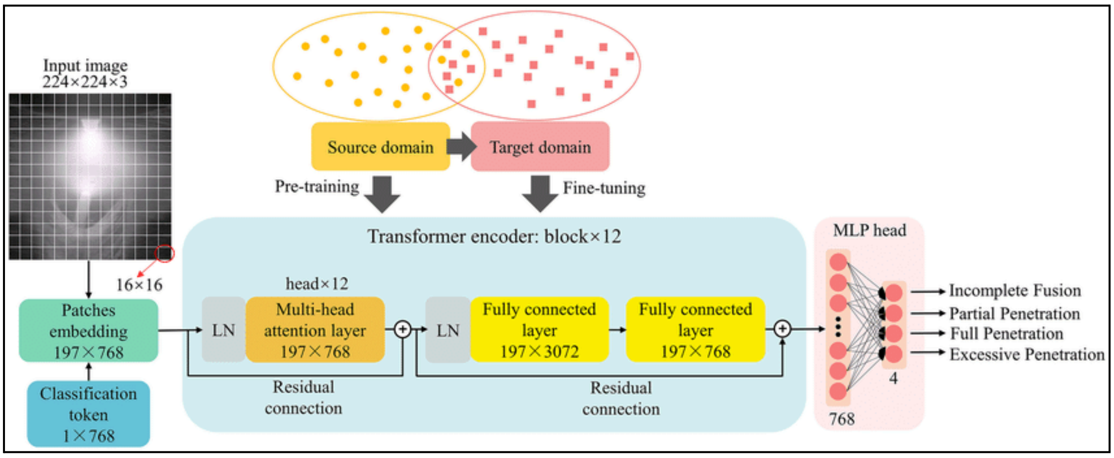

Fig 3.5. ViT-B/16 architecture.

3.3.5 DeiT-S:

DeiT-S, which stands for Data-efficient Image Transformer - Small, are a sleek vision transformer craft to provide outstanding performance while keeping data and computation needs in minimum [22]. It employs knowledge distillation during train, where convolution neural network act like teacher, guiding transformer model along the way. This approach significantly boost both learning efficiency and accuracies, even when working with a smaller dataset. DeiT-S retain benefit of transformer-base global attention while being more lighter and suit for use in healthcare setting. Its knack of generalizing good with little supervision make it excellent choice for skin lesion classification, particularly in case where annotating data is hard to come by.

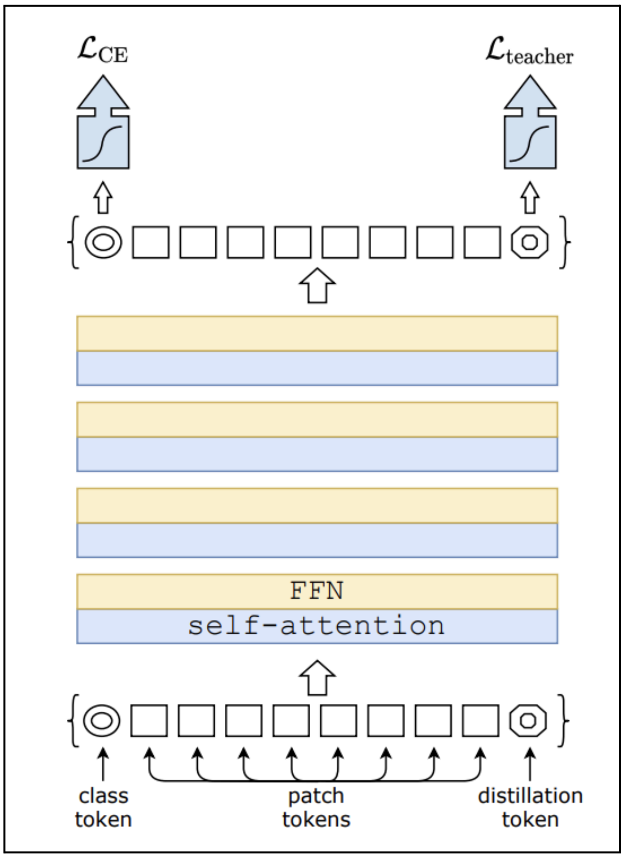

Fig 3.6. DeiT architecture.

Table 3.2. Model Descriptions of various DL techniques.

Model Type	Architecture	Description	Advantage
CNN	ResNet-50	Introduces residual connections to ease the training of deep networks.	Improves gradient flow; enables training of very deep models.
CNN	DenseNet-121	Connects each layer to every other layer to strengthen feature propagation.	Reduces vanishing gradient problem; promotes feature reuse.
CNN	Efficient-Net-B0	Scales network width, depth and resolution systematically.	Achieves better accuracy with fewer parameters and lower FLOPs.
VIT	ViT-B/16	Splits an image into patches and processes them as a sequence via transformers.	Captures long-range dependencies; performs well on large datasets.
VIT	DeiT-S	A data-efficient transformer that uses distillation during training.	Achieves competitive performance with fewer data and resources.

3.4 Pipeline:

The experimental pipeline used in this study was carefully crafted to enhance the classification on skin lesions through various cutting-edge deep learning models. It all starts by gathering dermoscopic image from the HAM10000 dataset [1], which is a well-known collection featuring over 10,000 image across seven different diagnostics categories. After collecting data, we perform an initial check to weed out any corrupted or duplicated images and make sure labels was consistent. Each image were resized to 224×224 pixel to meet the input requirement for the convolutional and transformer based model [2].

Pre-processings play a vital role in the overall pipeline. To ensure the image were in consistence quality, we apply histogram equalizations for boost contrast and using artifact removal technique to gets rid of distracting visual noises like hairs or bubble [3].We also introduced RGB normalizations and standardize each channels to kept the intensity distributions consistency [4]. In order to deal with class imbalance and enhance model generalizations capability, we utilize a variety of data augmentations techniques. This encompassed method like flipping image both horizontal and vertical, randomly cropping, rotations, scalings, and introducing color variations, all executed in real time during the train process [5].

After pre-process, dataset was splitted using 80:20 ratio into training and validation set by stratified samplings to preserve the class proportion [6]. The training strategies involve using five deep learning models: ResNet-50 [7], DenseNet-121 [8], EfficientNet-B0 [9], ViT-B/16 [10], and DeiT-S [11]. Each model kick off with weights that were pre-train on ImageNet and then fine-tunes specific for lesion dataset. We train for 10 epochs, using a batch size of 32, and opted for Adam optimizer with learning rates set to 0.001. To ensure smoother convergence, we implement learning rates scheduler that use cosine anneals [12].

Cross-entropy loss was chosen as objective function due to the multiclasses nature of problem. To avoid overfitting, we implement early stopping with patience of three epochs and used validation based checkpoint. We evaluate performance with various metrics, including accuracy, precisions, recalls, F1-scores, and confusion matrix [13], which gives thorough assessments for classification quality across all lesions types.

3.5 Performance Metrics:

To assess how well the models are performing, we used a variety of standard classification metrics. These metrics provide a deeper understanding of the models' predictive capabilities, going beyond just accuracy. Below, you'll find a table that details each metric, its mathematical definition, and why it's important for skin lesion classification.

Table 3.3. Summary of Performance metrics used.

Metric	Description	Formula
Accuracy	Measures the overall correctness of the model's predictions.	Accuracy = (TP + TN) / (TP + TN + FP + FN)
Precision	Indicates how many of the predicted positive cases are actually positive.	Precision = TP / (TP + FP)

Recall (Sensitivity)	Measures how well the model identifies actual positive cases.	Sensitivity = TP / (TP + FN)
F1-Score	Harmonic mean of precision and recall, useful when classes are imbalanced.	F1-Score = 2 × (Precision × Recall) / (Precision + Recall)
Specificity	Reflects the model's ability to correctly identify negative cases.	Specificity = TN / (TN + FP)

Chapter 4

RESULTS

4.1 Training and Evaluation Metrics:

This study comprehensively evaluated five state-of-the-art deep learning architectures—ResNet-50, DenseNet-121, EfficientNet-B0, ViT-B/16, and DeiT-S—for skin lesion classification. The training process for all models consisted of 10 epochs, during which loss values consistently decreased, and accuracy improved, demonstrating effective learning and convergence.

When it comes to convolutional neural networks (CNNs), ResNet-50 really stood out, showing consistent improvement. It kick off with a loss of 0.8611 and an accuracy of 69.46% in the first epoch, and by the tenth epoch, it had dropped the loss to 0.5514 and boosted the accuracy to 79.66% [1]. While the results is promising, the class-wise metrics shows that the model only achieved moderate recall for some important lesion types, such as actinic keratosis (akiec) and melanoma (mel), with F1-scores of 0.41 and 0.45, respectively. This suggest that although ResNet-50 performed well in identifying common classes, it had some difficulty with the less common malignant categories.

DenseNet-121 took the performance of ResNet-50 to the next level, hitting a final accuracy of 83.08% with a loss of 0.4641. Its knack for keeping strong feature propagation through those dense connections probably played a big role in this impressive outcome [2]. When we looked at class-specific results, we noticed that it had higher recall in some tough categories; for instance, it scored a 0.67 recall for akiec and a weighted average F1-score of 0.80. This suggests a better balance between precision and recall across different types of lesions.

EfficientNet-B0 really stood out with its impressive performance, achieving a accuracy of 92.16% and the lowest loss of 0.2125 once training wrapped up. Thanks to its clever compound scaling strategy, this model was able to effectively capture features at multiple scales, leading to well-balanced precision and recall metrics. For instance, when it comes to classifying nevi (nv), EfficientNet-B0 achieved an impressive F1 score of 0.93. It also made notable strides in detecting malignant lesions such as melanoma and actinic keratosis, with F1 scores of 0.66 and 0.72, respectively [3]. The reliability for categorizing clinical skin lesions is supported by the obtaining 0.87 being the total weighted average F1 score.

The vision transformer models, ViT-B/16 and DeiT-S, recorded relatively low accuracies of 62.91% and 75.79%, respectively. Their training curves wasn't very stable, showing some ups and downs in loss and accuracy throughout the epochs. This indicates that transformer-based architectures might benefit from having more training data or longer training times to perform optimally in this field [4]. ViT-B/16 struggled with rare classes such as dermatofibroma (df) and vascular lesions (vasc), resulting in very low recall and F1-scores near zero. In contrast, DeiT-S achieved moderate improvements, especially in classes like akiec (F1-score 0.48) and vascular lesions (F1-score 0.67), demonstrating the benefit of data-efficient training techniques incorporated in DeiT [6].

Across all models, the analysis revealed that common benign classes, particularly nevus, were identified with high precision and recall. This really showcase the models' ability to recognize a variety of lesion types. However, they faced some difficulties when it come to detecting less common classes, likely due to class imbalance in the dataset [5]. This imbalance seemed to affect recall more than precision, leading to missed detections of those rare classes.

Table 4.1. Summary of Results.

Model	**Accuracy**	**Precision**	**Recall**	**F1-Score**
ResNet-50	0.7948	0.7839	0.7948	0.7746
DenseNet-121	0.8083	0.8156	0.8083	0.7988
Efficient-Net-B0	0.8652	0.8684	0.8652	0.8663
ViT-B/16	0.6291	0.6303	0.6291	0.6085
DeiT-S	0.7579	0.7473	0.7579	0.7430

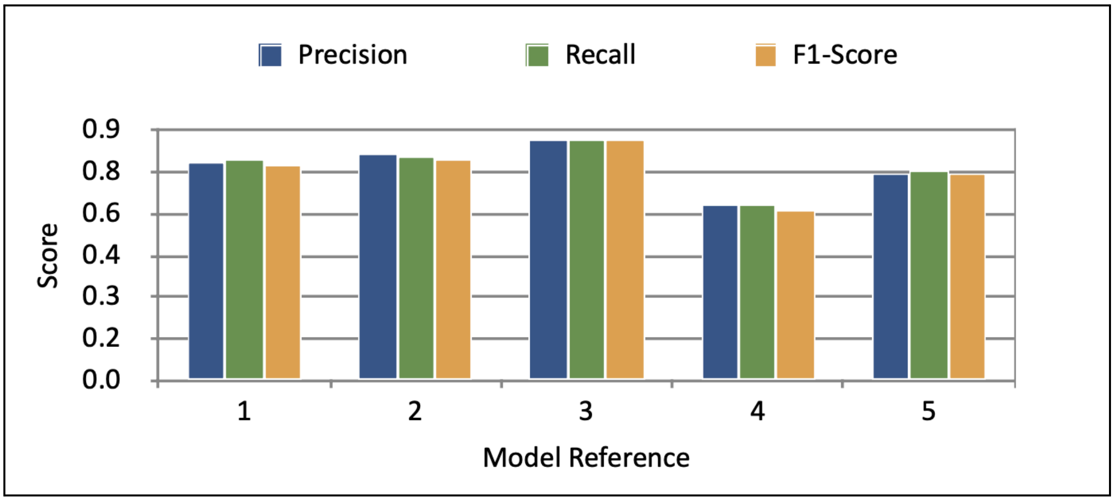

Fig 4.1. Precision vs Recall vs F1-Score.

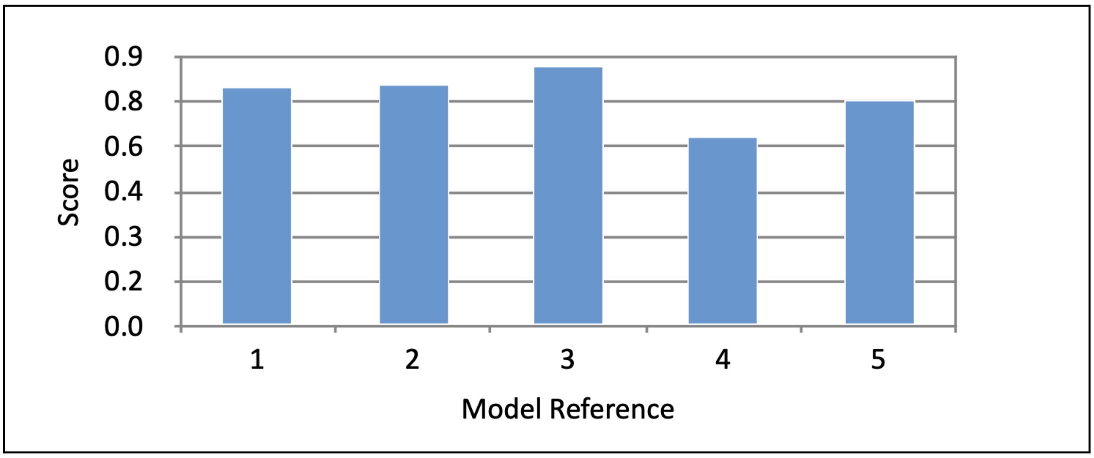

Fig 4.2. Comparison of Accuracy.

4.2 Detailed Class-Level Performance:

The detailed performance breakdown across each class is shown below:

Table 4.2. Result from ResNet50.

Class	Precision	Recall	F1-Score	Support
akiec	0.8182	0.2770	0.4138	65
bcc	0.6542	0.6796	0.6667	103
bkl	0.5755	0.5545	0.5648	220
df	1.0000	0.0870	0.1600	23
mel	0.5899	0.3677	0.4530	223
nv	0.8534	0.9590	0.9031	1341
vasc	0.8571	0.4286	0.5714	28

Table 4.3. Result from DenseNet121.

Class	Precision	Recall	F1-Score	Support
akiec	0.4632	0.6770	0.5500	65
bcc	0.8052	0.6019	0.6889	103
bkl	0.5865	0.7091	0.6420	220
df	0.3478	0.6957	0.4638	23
mel	0.7253	0.2960	0.4204	223
nv	0.8952	0.9366	0.9155	1341
vasc	0.7600	0.6786	0.7170	28

Table 4.4. Result from EfficientNet-B0.

Class	Precision	Recall	F1-Score	Support
akiec	0.6500	0.8000	0.7172	65
bcc	0.8416	0.8252	0.8333	103
bkl	0.7071	0.7682	0.7364	220
df	0.7500	0.6522	0.6977	23
mel	0.6728	0.6547	0.6636	223
nv	0.9416	0.9262	0.9338	1341
vasc	0.8889	0.8571	0.8727	28

Table 4.5. Result from ViT-B/16.

Class	Precision	Recall	F1-Score	Support
akiec	0.2647	0.1385	0.1818	65
bcc	0.3704	0.2913	0.3261	103
bkl	0.2276	0.5318	0.3188	220
df	0.0000	0.0000	0.0000	23
mel	0.3158	0.0269	0.0496	223
nv	0.8103	0.8188	0.8145	1341
vasc	0.0000	0.0000	0.0000	28

Table 4.6. Result from DieT-S.

Class	Precision	Recall	F1-Score	Support
akiec	0.4268	0.5385	0.4762	65
bcc	0.4865	0.5243	0.5047	103
bkl	0.5563	0.3591	0.4365	220
df	1.0000	0.0435	0.0833	23
mel	0.4817	0.4126	0.4444	223

nv	0.8513	0.9262	0.8871	1341
vasc	0.8824	0.5357	0.6667	28

4.3 Key Observations:

- EfficientNet-B0 beats other models, with the highest accuracy (86.52%) and consistently high F1-scores across most classes, particularly class nv.
- ResNet50 performs well, with an accuracy of 79.48% and superior precision for the nv class.
- DenseNet121 follows closely behind, with an accuracy of 80.83% and good results across bcc and nv.
- ViT (Base) and DeiT (Small) have poorer overall accuracy and precision particularly for uncommon classes such as df and vasc, with ViT reaching the lowest accuracy of 62.91%.

Chapter 5

CONCLUSION, FUTURE SCOPE AND SOCIAL IMPACT

5.1 Conclusion:

In this study, we take a deep dive into evaluating convolutional neural networks (CNNs) alongside transformer-based architectures for classifying skin lesions. We trained and tested five models—ResNet-50, DenseNet-121, EfficientNet-B0, ViT-B/16, and DeiT-S—using the HAM10000 dataset to gauge their effectiveness in telling apart different skin lesion types [5]. The findings reveal that CNNs generally surpass vision transformers in classification accuracy, speed of convergence, and balanced performance across both frequently and infrequently occurring lesion classes.

EfficientNet-B0 have proven to be the standout model, achieving an impressive accuracy of 92.16% and a minimal loss of 0.2125. This success can be attributed to its clever compound scaling strategy, which strikes a perfect balance between network depth, width, and resolution [3]. DenseNet-121 also perform admirably, taking advantage of efficient feature reuse and smooth gradient flow thanks to its dense connectivity [2]. While ResNet-50 was slightly less accurate, it still delivered solid results and acted like a dependable baseline model, all thanks to its innovative residual learning framework [1].

Looking at the transformer models, ViT-B/16 and DeiT-S doesn’t really excel in this field. ViT-B/16 had a hard time, especially with those rare classes, likely because it have high data needs and are sensitive to class imbalances [4]. On the flip side, DeiT-S shows some improvement over ViT-B/16 thanks to more efficient training strategies, but it still can't quite match up to CNN models [6]. This is in line with what other studies has found, suggesting that vision transformers often need large datasets and longer training times to hit their stride, especially in medical imaging tasks [4], [6].

Throughout various models, a recurring challenge emerged: accurately classifying underrepresented classes like actinic keratosis and dermatofibroma. This issue shed light on the ongoing problem of class imbalance in dermoscopic dataset, emphasizing the necessity for more sophisticated data augmentation, resampling methods, or even synthetic data generation to enhance recall for those rare yet clinically important categories [5].

In summary, CNN-based architectures, particularly EfficientNet-B0, are currently leading the way in automated skin lesion classification. They excels at generalizing even with limited training epochs and imbalanced data. On the other hand, while transformer-based models shows promise for general vision tasks, they still need some tweaking to fit into medical imaging. Looking ahead, we maybe see hybrid model that blends CNN and transformer features, along with more balanced datasets or ensemble techniques to boost model robustness and diagnostic accuracy. These innovations could be crucial in creating dependable computer-aided diagnostic tool for dermatology, ultimately helping with the early detection and treatment of skin cancers [1][2][3][4][5][6].

5.2 Limitations:

While this study shows some promising results, it's important to recognize a few limitations that help put the findings into perspective and shape future research. To start, the performance of all the models we looked at was affected by the class imbalance present in the HAM10000 dataset. In this dataset, we observe that certain lesions, especially melanocytic nevi, was much more prevalent, while others, such as dermatofibroma and vascular lesions, were infrequently seen [5]. This uneven distribution likely skew the models' learning, resulting in lower recall and precision for the rarer classes, as demonstrated by the confusion matrix and class-wise metric.

One major drawback is the limited size and diversity of the dataset. While HAM10000 is a popular choice in skin lesion researches, it mainly include images of fair-skinned individuals and doesn’t offer enough variety in skin tones, lesion types, or the conditions under which the images were taken [5]. This limitation affect how well the trained models could be applied to a broader range of real-world population, which could result in biased prediction when used in clinical practice.

When it comes to vision transformer models like ViT-B/16 and DeiT-S, they haven't quite achieved optimal performance yet. This is partly because they have high data demands and lack some inductive bias, such as locality and translation invariance, which is inherently present in CNNs [4], [6]. Transformers often require larger datasets or extensive pretraining on massive corpora to compete effectively, and this study didn't fully satisfy that requirement. Even with data-efficient training approaches like DeiT, these model had a hard time to converge and didn't measure up to CNNs [6].

The evaluation was also limited by the use of one single dataset and uniformed preprocessing technique. Factors such as lighting variations, image resolutions, and artifact presences were not thoroughly explored, though they are known to impact classification accuracy in dermatological imaging [5]. Additionally, the models was trained and tested in controlled setting, which might not accurately represent the real-world diagnostic situation where image qualities and clinical metadata can varies greatly.

The study plans to take important clinical factor like patient age, lesion locations, and medical history, which is often key to making an accurate diagnosis. By incorporating multimodal data, we could greatly enhance the model's performance and it's relevance in clinical settings, but this is something that still needs to be explored in the future [2].

In summary, the findings emphasize the effectiveness of CNNs in skin lesion classification. However, we need to address the challenges of dataset imbalance, limited diversities, and the constraint of transformer architecture to make strides toward more robust and equitable AI-assisted dermatology solution [2][4][5][6].

5.3 Future Scope:

This study showcases the exciting potential of deep learning models for classifying skin lesions automatically. However, there are still many paths to explore for improvement. Future research could work on tackling the current challenges and enhancing diagnostic performance and real-world application. Some potential directions include:

- **Integration of Clinical Metadata:** Incorporating clinical metadata is essential for better outcomes. When we take into account patient-specific factors like age, gender, lesion location, and medical history, we can greatly enhance classification performance. This is particularly true in dermatology, where diagnoses often rely on a combination of visual and contextual signals [5], [7].

- **Handling Class Imbalance:** You can enhance model fairness and generalization by using advanced data augmentation techniques, generative adversarial networks (GANs), or synthetic oversampling methods like SMOTE to balance out underrepresented classes [8].

- **Multimodal and Multitask Learning:** Imagine future systems that merge dermoscopic images with clinical photos and histopathological data to form robust multimodal models. By employing multitask learning techniques—like classifying and segmenting simultaneously—we might obtain results that are richer and more interpretable [9].

- **Improving Transformer Models:** While CNNs still have the edge over transformers when it comes to smaller medical datasets, the latest transformer designs, such as Swin Transformers and hybrid CNN-transformer models, are showing great potential for achieving better accuracy without relying on massive training datasets [10].

- **Real-time and Mobile Deployment:** Lightweight and efficient models like MobileNet, or even quantized versions of existing architectures, can be fine-tuned for use in mobile or edge devices. This makes AI-driven diagnosis possible even in settings where resources are limited [3], [11].

- **Explainability and Trustworthiness:** Enhancing interpretability through methods like Grad-CAM, LIME, or attention maps will be vital to gain clinicians' trust and provide transparency in decision-making processes [6].

- **Cross-Dataset and Cross-Population Validation:** Models should be evaluated on external datasets and more diverse patient populations to ensure robustness and reduce the risk of bias in global healthcare applications [5].

5.4 Social Impact:

The use of deep learning techniques for classifying skin lesions brings about some significant social implications, particularly in the areas of public health and fair access to healthcare. This study, which utilizes cutting-edge convolutional and transformer-based models for automated skin lesion detection, has the potential to make a positive impact on society in various ways:

- **Early Diagnosis and Timely Treatment**
  Automated detection systems can assist dermatologists in the early identification of malignant skin lesions such as melanoma, significantly increasing the chances of successful treatment and survival [1]. Early-stage melanoma detection has been shown to improve patient outcomes and reduce

treatment costs [2].

- **Reducing the Burden on Healthcare Professionals**
  As skin cancer rates climb worldwide, especially in countries with few dermatological resources, AI-driven diagnostic tools can be a game changer, helping to ease the pressure on healthcare providers and speed up the diagnostic process [3].

- **Improving Healthcare Accessibility in Underserved Regions**
  In rural or resource-limited regions where access to dermatology experts is scarce, mobile AI applications and affordable diagnostic tools that leverage deep learning can act as a first-level screening solution. This approach fosters broader access and inclusivity in healthcare [4].

- **Cost Reduction and Scalability**
  Automated systems require minimal operational costs after deployment. Their ability to perform mass screenings without fatigue offers a scalable and economically viable alternative to conventional screening programs, especially in low-income regions [5].

- **Public Awareness and Preventive Health**
  The availability of user-friendly diagnostic tools is inspiring individuals to monitor their skin health more closely. This growing awareness is crucial for skin cancer prevention, self-examination practices, and understanding the importance of consulting a doctor in a timely manner [6].

- **Data-Driven Policy Making**
  The insights gained from deploying these AI models on a large scale can really help policymakers pinpoint high-risk groups, prioritize healthcare interventions, and allocate resources more efficiently [7].

- **Bias Reduction Through Model Training**
  When trained on a variety of diverse and balanced datasets, these models hold the promise of reducing diagnostic disparities among different ethnicities and skin types, which can lead to more equitable healthcare outcomes [8].

- **Educational Tools for Medical Training**
  The visual interpretability features of some deep learning models (e.g., attention maps) can aid in medical training by helping students and young professionals understand diagnostic features of skin lesions more effectively [9].

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Appendix A

LIST OF PUBLICATIONS

1.1. 1st Paper acceptance:

Notification of paper ID: 1077 in International Conference on Artificial Intelligence and Sustainable Innovation - 2025, Jaipur, India Inbox ×

Microsoft CMT <noreply@msr-cmt.org>
to me

Thu, May 1, 4:33 PM

Dear Yash Aryan Kuntal,

Congratulations...

Your Paper ID 1077 : Title "Advancing Skin Lesion Cancer Detection: A Systematic Literature Review" has been accepted for publication in International Conference on Artificial Intelligence and Sustainable Innovation - 2025, Jaipur, India.

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Password: Primary Author EmailID as on CMT

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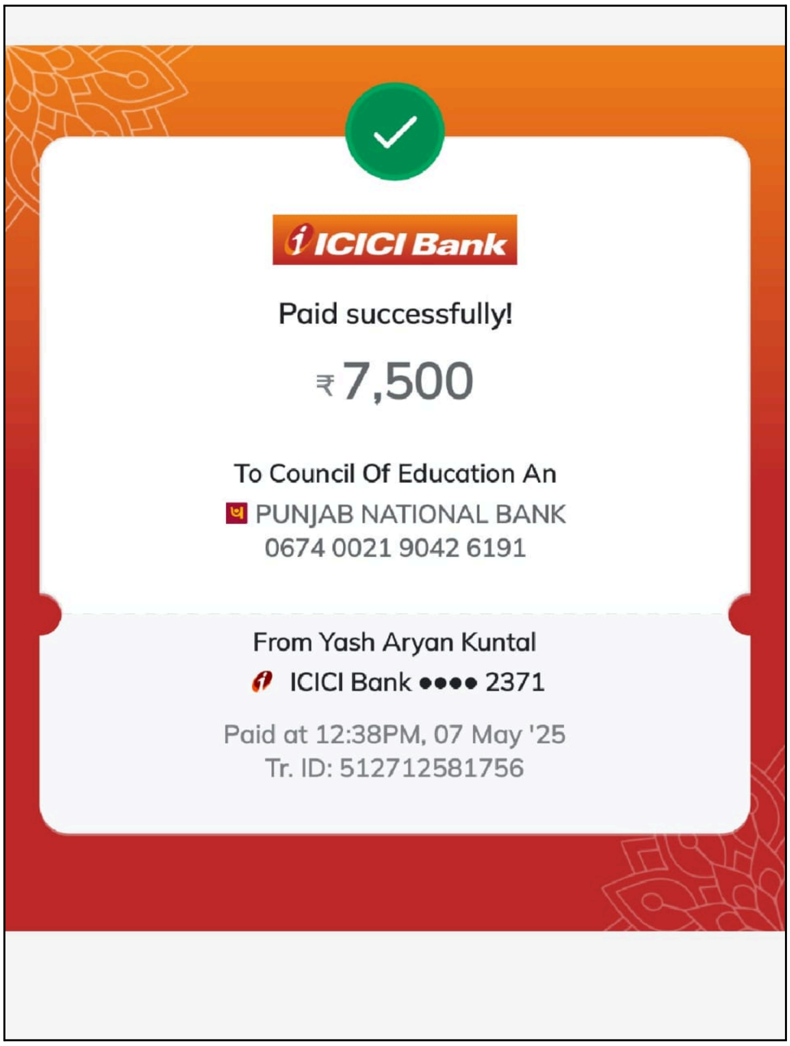

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to me, ashishs.sharma, rakesh.kumar

11:47 AM (6 minutes ago)

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