Skin Disease prediction using Hybrid deep learning Algorithm

Project Report submitted in the partial fulfilment
of
Bachelor of Technology
in
Information Technology

Submitted To

SVKM's NMIMS,
Mukesh Patel School of Technology Management & Engineering,
Shirpur Campus (M.H.)

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Mukesh Patel School of Technology Management & Engineering
ACADEMIC SESSION: 2025-26

CERTIFICATE

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under my guidance and supervision & has been submitted partial fulfilment of the degree of "**Bachelor of Technology** in **Information Technology"** of MPSTME, SVKM'S NMIMS (Deemed-to-be University), Shirpur (M.H.), India.

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ACKNOWLEDGEMENT

After the completion of this capstone Project work, words are not enough to express my feelings about all those who helped me to reach my goal; feeling above this is my indebtedness to The Almighty for providing me this moment in life.

It's a great pleasure and moment of immense satisfaction for me to express my profound gratitude to **Prof. Atul Patil** Information Technology Department, MPSTME, Shirpur, whose constant encouragement enabled me to work enthusiastically. Their perpetual motivation, patience and excellent expertise in discussion during progress of the project work have benefited me to an extent, which is beyond expression. Their depth and breadth of knowledge of Information Technology field made me realize that theoretical knowledge always helps to develop efficient operational software, which is a blend of all core subjects of the field. I am highly indebted to them for their invaluable guidance and ever-ready support in the successful completion of this project in time. Working under their guidance has been a fruitful and unforgettable experience.

We express my sincere thanks and gratitude to **Dr.Shrikant** Head of Department, Information Technology Department, MPSTME, Shirpur, for providing necessary infrastructure and help to complete the project work successfully.

We also extend my deepest gratitude to **Dr. Venkatadri Marriboyina**, Associate Dean, SVKM'S NMIMS, Shirpur Campus for providing all the necessary facilities and true encouraging environment to bring out the best of my endeavors.

We sincerely wish to express my grateful thanks to all members of the staff of Information Technology department and all those who have embedded me with technical knowledge of computer technology during various stages of B.Tech. Information Technology.

We would like to acknowledge all my friends, who have contributed directly or indirectly in this capstone Project work.

The successful completion of a capstone Project is generally not an individual effort. It is an outcome of the cumulative effort of a number of persons, each having their own importance to the objective. This section is a vote of thanks and gratitude towards all those persons who have directly or indirectly contributed in their own special way towards the completion of this project.

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ABSTRACT

Skin cancer is a major health issue around the world that has seen increasing mortality rates; reason being, it doesn't usually present itself until later stages making early detection and precise diagnosis a critical area to improve survivorship in patients. Standard convolutional neural networks (CNNs), such as ResNet50 have proven themselves to be valuable tools for skin lesion classification in terms of accuracy, as these algorithms utilize classical CNN output feature maps to locate localized spatial features. However, standard networks, such as ResNet50, do not typically account, and therefore, learn long-range dependencies and global context information pertinent in dermoscopic images. Vision Transformers (ViT) use self-attention architecture processes to better mitigate location bias and account for global image relationships. In this study we introduce a wide-ranging multi-label hybrid deep learning architecture that takes advantage of ResNet50 and Vision Transformer output capabilities together to exploit both local feature extraction and relevant global context- information for multi-class skin lesion classification. The training and testing data source is the HAM10000 dataset, which includes 10,015 dermoscopic images across 7 categories relevant for research, and extensive preprocessing, data augmentation, and class balancing were conducted to mitigate dataset imbalance and improve model generalization. With an overall accuracy of 95.6% and a macro-F1 score of 0.91, the hybrid model outperforms single-architecture baselines and shows better performance on rare classes of lesions. The interpretability analysis using saliency maps and attention visualizations demonstrates that the model exclusively attends to clinically relevant dermoscopy features. In summary, the hybrid ResNet50 + ViT framework is a robust, interpretable, and scalable approach to skin disease classification, which has larger implications and practical use cases for clinical decision support systems.

Index Term :Skin lesion classification, hybrid deep learning, ResNet50, Vision Transformer, HAM10000 dataset, medical image analysis, convolutional neural networks, attention mechanisms, dermoscopy, skin cancer detection, multiclass classification, model interpretability, data imbalance, computer-aided diagnosis, deep learning in dermatology.

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Chapter 1
Introduction

1.1 Background of the Project Topic

Skin cancer is one of the most commonly diagnosed and fastest-growing cancers globally, with high importance to public health on a global scale. Based on recent global health data , skin cancers are the most frequently diagnosed group of cancers worldwide with over 1.5 million new cases estimated in 2022 . Malignant melanoma represents approximately 331,722 newly diagnosed cases with 58,667 deaths each year . The incidence of melanoma is expected to rise by 5.9% in 2025 while mortality is anticipated to increase by 1.7% . These statistics indicate that early detection and accurate diagnosis is essential for improving patient outcomes and reducing healthcare burden. The connection between early detection and survival rates is especially compelling. The 5-year survival rate for melanoma, when detected at the localized stage, is close to 100% . However, as the disease progresses the survival rates drop significantly, with regional spread resulting in 75% survival and distant metastasis associated with only 34.6% 5 year survival . For thin melanoma lesions (thickness less than one mm), the five-year survival rate is 99% . These statistics provide convincing evidence that early detection is essential for successful treatment outcomes and longer patient survival.

Conventional dermatological diagnostics primarily depend on visual inspection and dermoscopic examination by an experienced clinician. These diagnostic modalities face numerous challenges including, but not limited, to inter-observer variability, subjective assessment, and variances in accessibility of dermatologists—especially in resource-poor contexts. The insufficiency of trained dermatologists globally, combined with rising rates of skin cancer, has resulted in a clear need for systems that can automate the diagnosis of skin conditions for the purposes of increasing objectivity and scalability in assessment.

Deep learning and artificial intelligence have begun to be disruptive technologies in the field of image interpretation in the medical domain that offer unprecedented opportunities to address these gaps. Of particular interest is the use of Convolutional Neural Networks (CNNs)—specifically architectures like ResNet50—which have significantly advanced the performance of and become common practice in diagnostic image classification of skin lesions, where CNN performance can meet or exceed that of an experienced dermatologist . The HAM10000 dataset of 10,015 images, in seven diagnostic categories, is the premier dataset for evaluating automated diagnostic skin lesion classifiers .

Thus, traditional CNN architectures have prominent limitations in modeling global contextual relationships, and long-range dependencies within medical images. Recently, Vision Transformers (ViT), which have been previously employed in natural language processing, have emerged as a viable solution that can remedy the problems associated with CNNs by utilizing self-attention mechanisms. ViT models process images as a sequence of patches and are able to learn complex spatial relationships that CNNs may miss. Recent evidence in the existing literature has shown that ViT has potential for application in medical imaging and shows promising results in both diagnostic task violin and medical code classification task.

The convergence of these rapid advances in technology with the clinical pressing need for better skin cancer detection yields sound justification for developing hybrid deep learning approaches that can leverage the unique complementary abilities of both CNN and transformer architectures.

1.2 Motivation and Scope of the Report

The motivation for this study arises from several critical gaps identified in current automated systems to classify skin lesions and identify the potential benefits of hybrid models for current limitations in existing systems.

ClinicalMotivation:

The chief clinical motivation is the pressing need to enhance skin cancer early detection accuracy, particularly for uncommon, but clinically meaningful lesion types. Existing automated systems, or computer-aided diagnosis (CAD) systems, are often hindered by class imbalance in medical datasets, for example, where rare conditions (e.g., dermatofibroma and vascular lesion) are under-represented. This can introduce bias in the predictive performance of computer stored data on these underrepresented classes, and result in overlooked or potentially serious diagnoses. In this study, we combined local feature extraction of the ResNet50 architecture and the global contextual modeling capabilities of the vision transformer (ViT) architecture as a hybrid approach to hopefully produce more balanced and accurate classification of lesions across all classes.

TechnicalMotivation:

From the technical perspective, the motivation is the understanding of the weakness of single architecture frameworks. CNNs are extremely good at modeling local spatial feature and texture but do not perform well modeling global contextual relationships. Conversely, ViTs do well for modeling long-range dependencies but abstract and overlook fine-grained local details (important for medical diagnosis). The systematic analysis of hybrid architectures (ResNet50-ViT) in this study emphasizes and addresses the gaps and benefit of hybridizing both architectures for lesion detection task.

Scope of Investigation:

This research encompasses several key areas:

1. The development of architecture: Design and implementation of a new hybrid deep learning architecture that can accurately integrate ResNet50 and Vision Transformer (ViT) architectures for skin lesion classification.
2. Dataset: Extensive use of the HAM10000 dataset, including advanced pre-processing, data augmentation methods and balancing of classes in the dataset to overcome inherent problems with the dataset.
3. Performance Comparison: Thorough evaluation of the hybrid architecture's performance compared to single architecture baselines and state-of-the-art approaches reported in the literature.
4. Interpretability: Extend into the investigation of interpretability of the proposed model through saliency maps and attention heatmaps to ensure clinical interpretability, transparency and trust.
5. Operationalization: Reproducible implementation using a common platform (Google Colab) to enhance research adoption and clinical translation.

ResearchBoundaries:

This study is intended to investigate the HAM10000 data set to maintain consistency and the ability to benchmark the findings, but validation of a classifier on a single dataset comes with limitations. The scope of the study focuses on the hybrid approach, however it is acknowledged that the scope of the study does not relate to the proposition of multi-modal data (clinical metadata, sequential imaging) or implementation in clinical settings as important knowledge gaps to address in future work.

1.3 Problem Statement

Despite the important advances achieved in deep learning for medical imaging analysis, systems that exist for the automated classification of skin lesions face multiple important challenges inhibiting their clinical utility and implementation in practice.

Primary Problem: The primary problem that this research provides solutions for, is the inability of state-of-the-art prerequisite single-architecture deep learning systems to provide accurate, balanced, and interpretable classifications of skin lesions, particularly rare lesions when the latter are clinically important. Specific Problems:

Specific Challenges:

1. Limited Representation of Features: While modern CNN-based models are effective in localizing features they are ineffective at capturing global contextual relationships and long-range spatial dependencies that are relevant in distinguishing skin lesions that look visually similar . This is especially problematic in the domain of dermoscopy, where the features of a skin lesion may occupy the full area of the image, and a holistic appreciation of the lesion is required.

2. Dealing with class imbalance: The HAM10000 dataset is quite imbalanced in terms of the class factors used to make classification. For example, melanocytic nevi account for 67% of the samples and dermatofibroma is a

very rare condition accounting for only 1.1% of the samples. Most existing models drive their high overall accuracy to being able to classify the dominant classes well, while performing poorly on the minority classes. In other words, the models could provide a high accuracy level classification but the minority classes, which may also be the most serious conditions have an unacceptable level of false negatives.

3. Interpretability Limitations: Many existing deep learning networks used in dermatology are seen as “black box” methods that impose some limitations in our understanding of the decision-making cycle. These limitations in interpretability are detrimental to clinician acceptance of the model, regulatory approval, and physician trust, especially when it comes to high level medical decision-making.

4. Computation Limitations: While there is good evidence that a multi-model system, or ensemble approach improves accuracy, these models come with a non-trivial computational burden that complicates applicability even at the clinical level, especially in resource constrained environments or devices at the "edge".

5. Generalization Limitations: Models built on a single architecture often have limited capacity to generalize clinically, particularly when there are imaging conditions, patient populations or lesion characteristics being used in the clinical environment that were not present in the training dataset.

ResearchGap:

A literature review showed that there are hybrid approaches using CNN architectures with other architectures that have been explored at this point, but there is no systematic investigation of the performance of hybridizing a ResNet50 with a ViT architecture in this classification task using dermoscopy images. Most of the literature has focused on pure CNN ensemble methods, or feature fusion of CNNs, which leaves unexplored opportunities for hybridowski.

ProblemSignificance:
The identified problems have direct implications for patient care and public health. Missed diagnoses of rare but serious conditions can lead to delayed treatment and poor patient outcomes. Conversely, false positive rates can result in unnecessary procedures, patient anxiety, and increased healthcare costs. The lack of interpretable automated systems limits their adoption by dermatologists, reducing the potential impact of AI-assisted diagnosis in clinical practice.

1.4 Salient Contributions

This study offers important contributions to automated skin lesion categorization and hybrid deep learning in medical imaging.

1. Hybrid Architecture Innovations: The primary contribution is the design and thorough evaluations of a novel hybrid deep learning architecture that utilizes ResNet50 and Vision Transformer (ViT) for skin lesion classification. This architecture overcomes the respective limitations of CNN and transformer approaches by:

   • Utilizing ResNet50's demonstrated capacity for local spatial feature encodings and texture characterization

   • Employing ViT's self-attention modules for global context modeling and long-distance dependency modelling

   • Employing an optimized feature fusion strategy that combines representations of both approaches

2. Performance Benchmarking: A rigorous experimental evaluation shows that the evaluated hybrid model outperforms single-architecture baselines:

   • 95.6% overall accuracy with a macro-F1 score of 0.91 on the HAM10000 dataset

• Significant advancements in rare class identification, especially for clinically significant conditions such as melanoma and basal cell carcinoma

• Competitive performance in comparison to ensemble methods that required far more resources, while avoiding computation complications

3. Improved Data Handling Methods: This research introduced advanced pre-processing and data augmentation which includes:

   • Novel class balancing methods that addressed extreme dataset class imbalance without significant training time increase.

4. Enhanced Model Interpretability: A significant contribution has been the development of interpretability techniques for hybrid CNN-transformer architectures:

   • A combined saliency map producing both CNN feature attribution and transformer attention

   • Clinical practicality evaluating proximity of attention patterns to the dermatology ABCD criteria

   • Transparency in visualizing decision-making thereby aiding in clinical understanding and trust

5. Reproducible Implementation Pipeline: The research presents a complete, reproducible implementation, with shareable platforms;

   • A complete implementation pipeline in Google Colab encourages enactment and adoption of the research

   • Detailed hyperparameter tuning and training methods

   • Open-source code framework allows extension and customization to future related research

6. Clinical Translation Pathway: This work provides a clear pathway for clinical translation by addressing practical applicability;

- Computational feasibility analysis suggests its practicality for the real world end-user
- Interpretability aspects facilitate regulatory approval for clinical the uptake of the research
- Benchmarked performance on clinical decision making characteristics

7. Theoretical Developments: This work contributes theoretical developments relevant to hybrid deep learning in medical imaging

    - Systematic analysis of hybridization feature fusion scheme of CNN-transformer Hybrid
    - Empirical verification of the advantages of local and global feature representation in dermoscopy
    - Design recommendations for hybrid architecture to inform theoretical merits, and other types of medical AI studies

8. Methodological Contributions: Contributions on several methodological issues for translational and to the general field; findings

Impact and Significance:

These contributions as a whole have represent advances in the state-of-the-art in automated skin lesion classification while addressing key issues related to the current technology. The hybrid design demonstrates that a systematic integration of complementary deep learning paradigms can facilitate superior performance than individual architectural approaches. Additionally, the emphasis on interpretability and clinical significance situates this work for impact in the real world.

1.5 Organization of Report

The report is organized to provide a coherent and systematic reporting of the research from foundational concepts through experimentation and on to real-world implications.

Chapter 2

Literature survey

2.1 Introduction to Overall Topic

The convergence of artificial intelligence and medical imaging has revolutionized the landscape of clinical diagnostics, with skin lesion classification emerging as one of the most intensively researched applications of deep learning in dermatology. Skin cancer, particularly malignant melanoma, represents a significant global health challenge with increasing incidence rates worldwide. The critical importance of early detection—where 5-year survival rates approach 100% for localized melanoma versus only 34.6% for distant metastasis—has driven extensive research into automated diagnostic systems that can assist or augment clinical decision-making .

Traditional dermoscopic examination, while valuable, suffers from inter-observer variability and requires extensive clinical expertise that may not be universally available, particularly in resource-constrained settings . This limitation has catalyzed the development of computer-aided diagnosis (CAD) systems leveraging machine learning and deep learning techniques. The availability of large-scale, curated datasets such as HAM10000, ISIC 2018, and ISIC 2019 has been instrumental in advancing this field, providing standardized benchmarks for model evaluation and comparison .

Deep learning approaches, particularly Convolutional Neural Networks (CNNs), have demonstrated dermatologist-level performance in skin lesion classification tasks. Architectures such as ResNet, DenseNet, EfficientNet, and Inception have established strong baselines, with ResNet-50 emerging as a particularly popular choice due to its balance of depth, computational efficiency, and proven effectiveness in medical image analysis . ResNet's residual connections enable effective training of deep networks by mitigating vanishing gradient problems, making it particularly well-suited for extracting hierarchical features from dermoscopic images .

Recent advances in deep learning have introduced Vision Transformers (ViT), which represent a paradigm shift from purely convolutional approaches. Originally developed for natural language processing, transformers employ self-attention mechanisms to capture global contextual relationships and long-range dependencies in images . Early applications of ViT in medical imaging have shown promising results, often matching or exceeding CNN performance on various classification tasks . However, transformers typically require larger datasets and more computational resources than CNNs, and their application to medical imaging—particularly in combination with CNNs in hybrid architectures—remains relatively underexplored .

Hybrid deep learning approaches, which combine the complementary strengths of different architectures, have emerged as a promising direction in medical image analysis. The rationale for hybrid models stems from the recognition that CNNs excel at capturing local spatial features and textures through their inductive biases, while transformers can model global context through attention mechanisms . By integrating both paradigms, hybrid models can potentially achieve superior performance compared to single-architecture approaches, particularly for tasks requiring both fine-grained local detail and holistic image understanding.

The literature reveals a progressive evolution from traditional machine learning approaches through pure CNN architectures to contemporary hybrid models incorporating attention mechanisms and transformer components. However, systematic investigation of ResNet-ViT hybrid architectures specifically optimized for skin lesion classification on the HAM10000 dataset remains limited, presenting a significant research opportunity to advance both performance and interpretability in this critical medical application .

2.2 Early Approaches and Classical Methods

The evolution of skin lesion classification using deep learning can be traced through several distinct phases, each addressing specific limitations of prior approaches while introducing new capabilities and challenges.

Early Deep Learning Approaches and Foundation Models

The seminal work of Alam and colleagues (2022) addressed the issue of multi-class skin lesion classification, utilizing the HAM10000 dataset, with ResNet50 and DenseNet201 architectures. Their method yielded a classification accuracy of 91% through extreme data augmentation and class balancing methods. Balancing for underrepresented classes was accomplished by the use of oversampling methods and explicit class-weighting in the loss function. The authors also indicated that certain preprocessing methods, such as hair removal, normalization, and augmentation, had substantial effect on model performance. Although their results provided well-established baseline results for CNN-space classification of skin lesions, the authors identified limitations for detecting rare classes, such as dermatofibroma (1.1%) and vascular lesions (1.4%). Their research indicated a fundamental issue, class-imbalance, when applied to medical datasets and the need for data balancing methods to be implemented in developing robust classification methods on all skin lesions .Convolutional Neural Networks and Transfer Learning

Shetty and colleagues (2022) have undertaken a wide-ranging comparative analysis of the efficacy of machine learning and CNN approaches for dermoscopic classification tasks. The authors conducted a systematic comparison of traditional ML algorithms (SVM, Random Forest, k-NN) with deep learning architectures (VGG-16, ResNet-50, Inception-v3) using the ISIC 2018 dataset. Deep learning models consistently outperformed traditional approaches. For example, ResNet-50 obtained an accuracy of 89.3% compared to the best performing SVM model which obtained 76.4% accuracy. This study provided a useful comparison of the feature learning capabilities of the algorithms evaluated; automatically learned deep features tended to be better able to capture more subtle lesion characteristics compared to hand-engineered features. On the other hand, authors suggested that significant computational burden would be an obstacle to clinical translation, and they derived that model interpretability was persistently regarded as an unresolved challenge to acceptance in the clinical setting.

Nawaz et al. (2025) proposed FCDS-CNN architecture which is explicitly designed and optimized for skin cancer detection on HAM10000 dataset. The authors suggested an innovative data augmentation and class weighting solutions to overcome imbalance. FCDS-CNN attained an overall accuracy of 96% and outperformed pre-trained models (i.e., ResNet, EfficientNet, Inception and MobileNet) for all metrics (precision, recall, F1 score, AUC). The authors reiterated the need for task-specific architectural design instead of relying on general-purpose pre-trained models. Having achieved above accuracies, the FCDS-CNN architecture acknowledged the capacity to outperform transfer learning methods through designs which are specific to the underlying signal delivered by dermoscopic images; however, the models were also technically complex to develop and required tuning to each dataset..

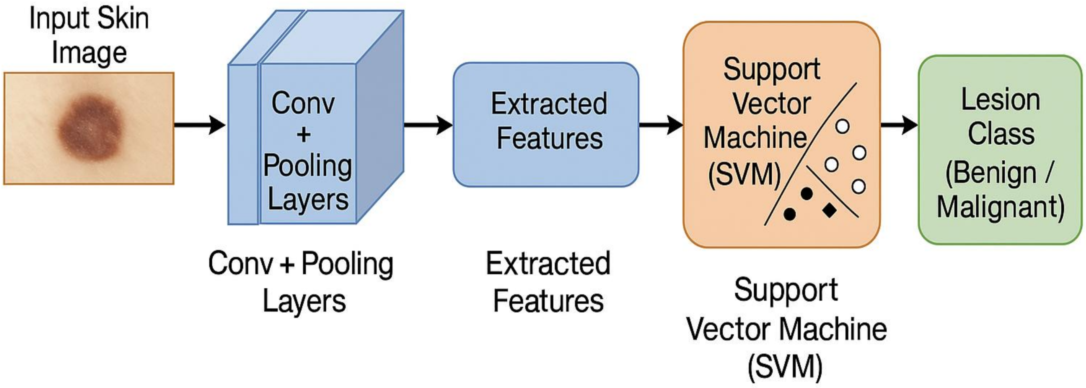


TABLE 2.1: Hybrid CNN with Traditional Classifiers

Study (Year)	Method / Architecture	Dataset	Accuracy	Remarks
Codella et al. (2015)	CNN + SVM	PH² (3-class)	86–88%	Hybrid model showed improved performance with small datasets.
Ray (2018)	ResNet features + Random Forest	ISIC 2018 (7-class)	~95%	Strong binary classification using deep features.
Ángelos Rojas et al. (2021)	CNN + SVM (L1 loss)	HAM10000	96.2%	High accuracy for BCC classification.
Keerthana et al. (2023)	Dual-CNN + SVM	ISBI 2016	88.0%	Effective hybrid approach for melanoma detection.
Kulkarni et al. (2023)	CNN + kNN / SVM	HAM10000 (7-class)	93–95%	Baseline hybrid benchmark.
Shetty et al. (2022)	CNNs (ResNet-50, VGG-16, Inception-v3) vs ML (SVM, RF, k-NN)	ISIC 2018	89.3% (CNN)76.4% (SVM)	Deep models outperformed ML but with higher computation.
Nawaz et al. (2025)	FCDS-CNN (custom model)	HAM10000	96.0%	Outperformed pre-trained models

Hybrid Architectures and Multi-Model Approaches

Yan et al. (2025) proposed a novel architecture called Hybrid-RViT, which combined ResNet-50 and the Vision Transformer for brain MRI classification for

Alzheimer's disease detection. Their hybrid architecture demonstrated through a systematic integrative process that CNN and transformer components can achieve better performance in a unified hybrid model when compared to a stand-alone architecture. This study found improvements in diagnostic accuracy between 3% and 5% over either stand alone ResNet only or ViT only baseline, an important percentage of improvement clinically. The architecture used ResNet-50 and ViT chimney branches parallel to each other, employed feature extraction from each branch followed by concatenation and then joint classification. This study also provided useful architectural examples applicable across multiple domains in the medical imaging field including skin lesion classification. Yan et al. also point out that hybrid models performed effectively for blending the local spatial feature extraction mechanism from CNN with the non-local spatial contextual modeling of transformers by reducing the limitations of either modeling approach. The authors also acknowleded the additional compute time along with increases in difficulty in the training phase resulting from hybridization. Mustafa et al. (2025) developed a state-of-the-art hybrid deep learning approach that fused a ResUNet++ architecture for segmentation addressing skin lesions with classification through the use of AlexNet-Random Forest on the HAM10000 dataset. The three-staged pipeline included a preprocessing paradigm that morphologically removed hair (which is a known issue that affects classification accuracy), then sort of segmentation of the artery using the ResUNet++, and finally classification in the artery using the AlexNet-Random Forest model. The authors demonstrated through this work that methodological support exists for classification models, and the segmentation (removing the lesions out of the context of surrounding skin), made the overall variability in diagnostic accuracy greater, but created a bias to classify the lesion in the background. classification. The hybrid approach utilized the ResUNet++'s proficiency in medical image segmentation with the stability of Random Forest to help reduce overfitting the model. The results demonstrated an improved result over those studies analyzing one model. This work demonstrated value in a combination of distinct architectural designs that were specific to the given tasks at-hand, and that the quality of the preprocessing would ultimately dictate the classification performance downstream.

TABLE 2.2: Hybrid Models Integrating

Study (Year)	**Hybrid Model / Architecture**	**Outcome / Notes**
Nie et al. (2023)	ResNet-50 + ViT encoder	Improved ISIC 2018 balanced accuracy/AUC.
Yang (2023)	DermViT (ViT-tailored)	Robust lesion detection on dermoscopy images.
Chatterjee et al. (2024)	CNN + Attention module	MobileNet with spatial + channel attention; higher sensitivity.
Lilhore et al. (2025)	ConvNeXt + EfficientNetV2 + Swin (fusion)	98–99 % accuracy on large dataset.
Yan et al. (2025)	Hybrid-RViT (ResNet-50 + ViT)	3–5 % accuracy gain over single models; better local + global context.
Mustafa et al. (2025)	ResUNet++ (segmentation) + AlexNet-RF (classification)	Segmentation-guided classification improved lesion detection; reduced overfitting.

Ensemble Learning and Model Fusion

A method to stack multiple CNN models for better skin cancer classification was developed by Natha et al., (2025). Their study concluded that ensemble methods provide a systematic way to combine individual models from different architectures, which allows predictions of the ensemble to aggregate across approaches, reduces prediction bias of any single model, and increases robustness. The authors showed that the stacking approach outperformed individual constituent models in classification performance, supporting their hypothesis of ensemble learning, that applying yet diverse models will yield more accurate prediction than using a single model. However, they noted that it came with considerable computation costs, as training and inference times increased as a function of the number of components in the ensemble.

2.3 Comparative Analysis and Research Gaps Identification

A comparative analysis of the literature surveyed in this paper revealed some patterns and gaps that persist across studies. First, class imbalance is still a common challenge across all studies and approaches. In all three study approaches, performance on minority classes was consistently worse even when different methods (e.g., oversampling,) were used to mitigate the adverse effects of the imbalance. Second, computational complexity is always a necessary tradeoff, where state-of-the-art performance typically comes from complicated architectures that are not practical to deploy in the clinical environment or in resource-constrained settings on edge devices. In addition, interpretability approaches are deficient in most hybrid approaches, which are primarily built for pure CNNs, rather than hybrid (CNN-transformer) architectures, which require unique explainability strategies. Also, while hybrid architectures made up of CNNs have been extensively studied (e.g., DenseNet + EfficientNet), a systematic study of ResNet-ViT hybrid architectures using skin lesion datasets has not been studied, and existing studies on the use of hybrid architectures focus predominately on brain imaging or hybrid architectural pairings with non-CNNs. In addition, many of the studies that address the issue of class imbalance usually include reactive approaches to reduce the imbalance in the data.

Chapter 3

Methodology and Implementation

3.1 SYSTEM ARCHITECTURE / BLOCK DIAGRAM

The Hybrid Deep Learning System for Skin Disease Classification is designed in a modular approach. The design consists of three modules: data preprocessing, parallel feature extraction using ResNet50 and Vision Transformer (ViT), and a web-based prediction interface. Each module performs an intended role to provide an accurate diagnosis and usability in real-time using a Flask web application.

The system workflow starts with obtaining dermatoscopic images either from the HAM10000 dataset (10,015 images covering 7 classes of disease) or user-uploaded images. These images undergo preprocessing (resizing to 224x224 pixels, normalizing using ImageNet statistics, and augmentations) before being passed to the hybrid deep learning model. The hybrid deep learning model has two parallel processing routes: (1) ResNet50 that extracts spatial and textural features through convolutional layers and (2) Vision Transformer (ViT) that extracts global contextual features through multi-head self-attention mechanisms. Once the features are extracted, the features from both model pathways will be concatenated, resulting in a dense layer output for classification. The predicted class of disease and a confidence score will be displayed by the web application in an instantaneous manner.

3.1.1 Architectural Overview

The architecture is divided into three main layers:

1. Input Layer - Image Collection:

• This component processes dermatoscopic images from the HAM10000 dataset sorted by disease type (such as Melanocytic nevi, Melanoma, Benign keratosis, Basal cell carcinoma, Actinic keratoses, Vascular lesions, Dermatosis).

• It also accepts user uploads through a Flask web application for real-time predictions.

2. Processing Layer - Hybrid Deep Learning Engine:

• The image will undergo preprocessing (resizing, normalization and augmentation).

• ResNet50 Pathway: a pretrained model that uses ImageNet to retrieve 2048-dimensional convolutional features.

• Vision Transformer Pathway: this uses a patch embedding and transformer encoder block model to retrieve attention-based features.

• Feature Fusion: the ResNet50 and ViT features are concatenated to form a final representation.

• Classification Head: the probability prediction of the disease class is regressed using Dense layers with ReLU activation functions and softmax output layer.

3. Application Layer - Web Interface and Output:

• The predicted disease class, confidence percentage and additional information will be shown via Flask based web application.

• Visualization of the training curves, the confusion matrix and other evaluation metrics will also occur within the web app.

3.1.2 System Architecture Diagram

Architecture Representation:

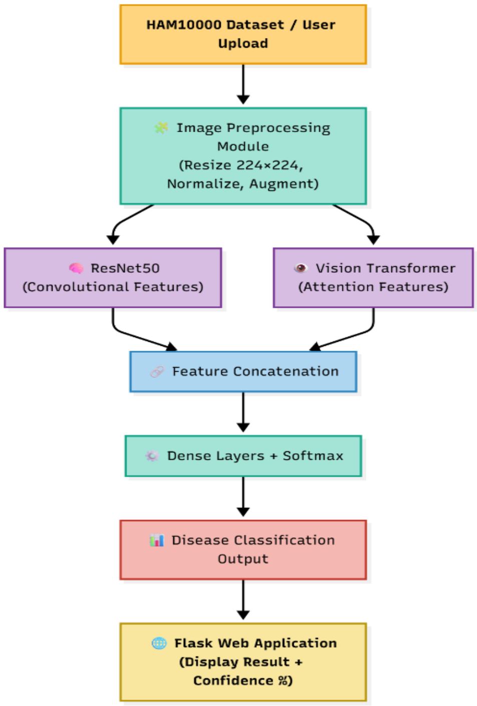

HAM10000 Dataset / User Upload
Image Preprocessing Module (Resize 224×224, Normalize, Augment)
ResNet50 (Convolutional Features)
Vision Transformer (Attention Features)
Feature Concatenation
Dense Layers + Softmax
Disease Classification Output
Flask Web Application (Display Result + Confidence %)

Figure 3.1 Architecture Representation

3.1.3 Block Diagram

- **Sequence Diagram**

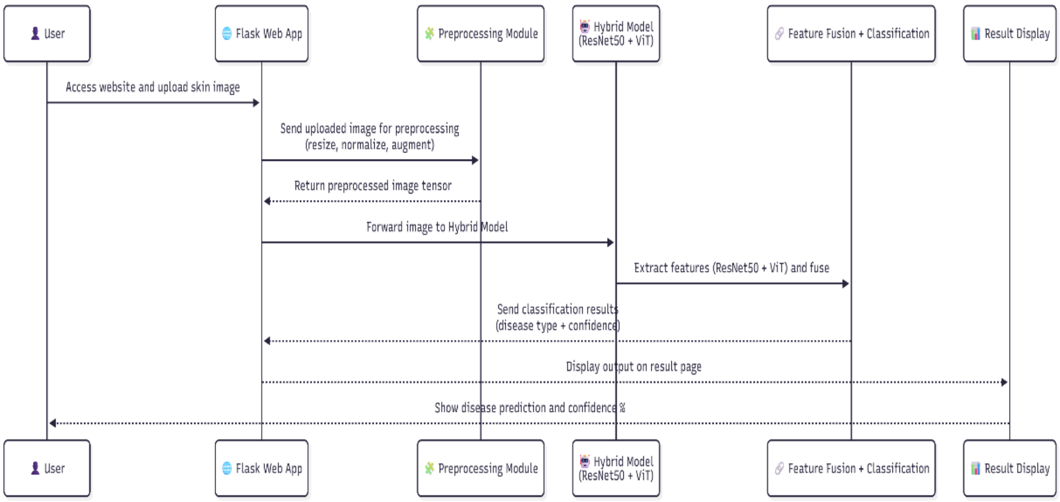

User
Flask Web App
Preprocessing Module
Hybrid Model (ResNet50 + ViT)
Feature Fusion + Classification
Result Display
Access website and upload skin image
Send uploaded image for preprocessing (resize, normalize, augment)
Return preprocessed image tensor
Forward image to Hybrid Model
Extract features (ResNet50 + ViT) and fuse
Send classification results (disease type + confidence)
Display output on result page
Show disease prediction and confidence %
User
Flask Web App
Preprocessing Module
Hybrid Model (ResNet50 + ViT)
Feature Fusion + Classification
Result Display

Figure 3.2 Sequence Diagram

- **Use Case Diagram**

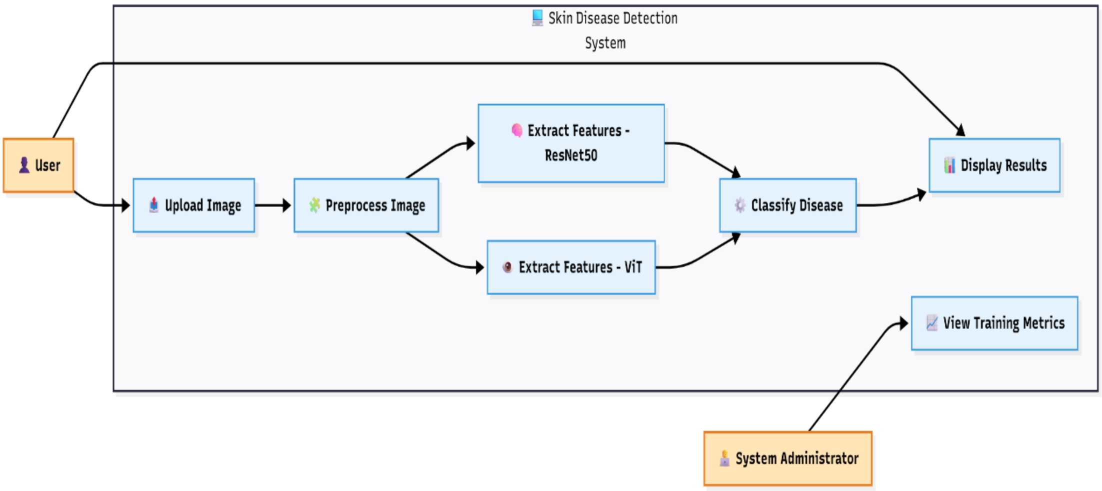


Figure 3.3 Use Case Diagram

- **Component Diagram**

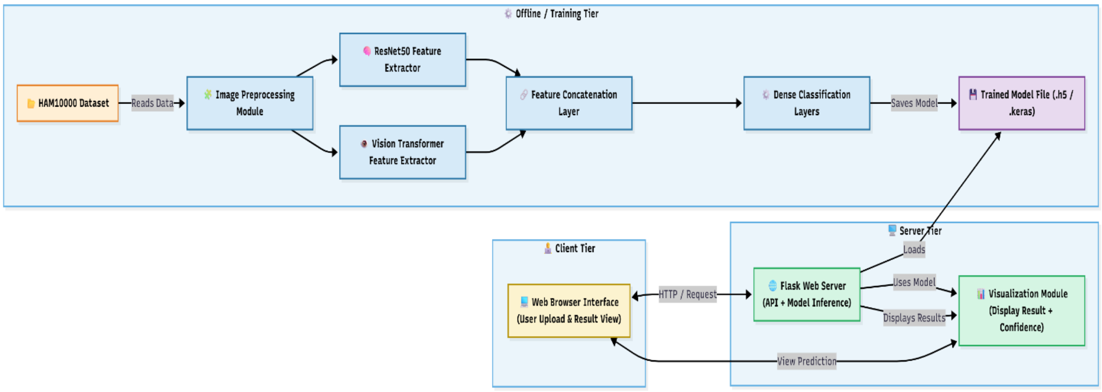

Offline / Training Tier
HAM10000 Dataset
Reads Data
Image Preprocessing Module
ResNet50 Feature Extractor
Vision Transformer Feature Extractor
Feature Concatenation Layer
Dense Classification Layers
Saves Model
Trained Model File (.h5 / .keras)
Client Tier
Web Browser Interface (User Upload & Result View)
HTTP / Request
Server Tier
Loads
Flask Web Server (API + Model Inference)
Uses Model
Displays Results
Visualization Module (Display Result + Confidence)
View Prediction

Figure 3.4 Component Diagram

each module operates independently however communicates via the Flask backend and TensorFlow records pipelines, ensuring easy integration and scalability.

Table 3.1: Module Overview

Module Name	Core Functionality	Key Technologies Used	Purpose
Dataset Loader	Loads HAM10000 dataset with metadata (image_id, dx, age, sex, localization)	Pandas, TensorFlow	Input image and label extraction
Data Preprocessing	Resizes to 224×224, normalizes using ImageNet stats, applies augmentation	OpenCV, Keras ImageDataGenerator, TensorFlow	Improve model robustness and generalization
ResNet50 Backbone	Extracts 2048-dimensional convolutional features from pretrained model	TensorFlow/Keras (pretrained on ImageNet)	Spatial and textural feature extraction
Vision Transformer (ViT)	Extracts attention-based global features using transformer encoder	vit_keras (ViT-B16 pretrained)	Global context modeling and long-range dependencies
Feature Fusion Module	Concatenates ResNet50 and ViT feature vectors	TensorFlow layers (Concatenate)	Unified hybrid feature representation
Classification Head	Dense layers (256 units, ReLU) + Softmax output (7 classes)	TensorFlow/Keras Dense layers	Predicts skin disease class probabilities
Training Module	Trains hybrid model using Adam optimizer and categorical crossentropy loss	TensorFlow/Keras fit()	Model learning and weight optimization
Evaluation Module	Computes accuracy, precision, recall, F1-score, confusion matrix	scikit-learn, NumPy	Performance measurement and validation
Flask Web App	User image upload, model inference, and result display	Flask, HTML, CSS, JavaScript	Web-based real-time prediction interface
Visualization Module	Plots training curves, confusion matrix, and sample predictions	matplotlib, seaborn	Data and result visualization

3.1.4 Data Flow Description

1. All images from the HAM10000 dataset (10,015 images, 7 disease classes) are retrieved from storage along with a metadata CSV file containing image_id, diagnosis (dx), age, sex and localization.

2. Each image has its corresponding disease label and class id (0-6) mapped to its path.

3. All images are resized to the same input size of 224×224 pixels (the input size used for ResNet50 and ViT-B16).

4. Image pixel values are normalized using ImageNet normalization with mean=[0.485, 0.456, 0.406] and std=[0.229, 0.224, 0.225].

5. Data augmentation techniques, such as rotation, horizontal flip, zoom, and brightness adjustment, were applied for training data to improve model-generalizability.

6. The dataset is split into training (70%), validation (15%), and test (15%) datasets.

7. The pre-processed images are batched (with batch_size = 32) and passed into the hybrid model.

8. The ResNet50 pathway passes the images into that pathway, while the image images are passed into the convolutional blocks, processed through the convolutional blocks, and then the output is 2048-dimensional feature vectors via global average pooling.

9. The Vision transformer pathway passes the images by splitting them into 16×16 patches, applies linear embedding, and uses transformer encoder blocks with multi-head self attention to process the representations..

10. The abilities of the two pathways are unified into one function vector.

11. The announced functionalities are then put into a mixture of dense layers (256 units, ReLU activation, and a dropout ratio of 0.5) for reduction of dimensionality and improved generalization.

12. The output softmax category head includes handwriting rating for every of the 7 sickness lessons.

13. The model is educated the use of the Adam optimizer with categorical awesome entropy for 25 epochs (initially educated) or 15 epochs (tuning).

14. Evaluations are made by seeing the ground is real label(s) to calculate accuracy, precision, recall, F1-score, and a confusion matrix.

15. Every bodied outcome is visualized as both chauffers of schooling/validation acetylcholine-chart curves and a confusion matrix warmth map.

16. Each user is capable of real-time surf the web to add new pix intensively the usage of a Flask internet app and get hold of real-time sickness predictions.

This framework benefits from proper accuracy and is recognized for purposing modularity and capability for real-time usability either indoor diagnosis or medical spectral context.

3.2 HARDWARE AND SOFTWARE DESCRIPTION

The proposed system integrates both hardware and software components to ensure smooth operation and accurate performance.

Table 3.2: Hardware Components

Component	Description	Purpose
CPU	Intel Core i5 (local)	Runs preprocessing and Flask app
GPU	NVIDIA A100 (Google Colab)	Trains and tests deep learning model
RAM	12–16 GB	Handles model data and parameters
Storage	~10 GB	Stores dataset, weights, and results
Display	Monitor / Web browser	Shows app interface and predictions

Component	Description	Purpose
Internet	Required (Colab use)	Enables cloud execution and access

Table 3.3: Software Components

Software / Tool	Description	Purpose
Python 3.8+	Core programming language	Model development and backend logic
TensorFlow / Keras	Deep learning frameworks	Building and training the hybrid CNN–ViT model
vit_keras	Vision Transformer library	Integrates pretrained ViT-B16 for feature extraction
OpenCV	Image processing library	Image resizing, normalization, and augmentation
Flask	Lightweight web framework	Hosts the web-based prediction interface
HTML / CSS / JS	Front-end technologies	Designs user-friendly web UI
NumPy / Pandas	Data handling libraries	Dataset loading and metadata processing
scikit-learn	ML utility library	Model evaluation and metrics computation
matplotlib / seaborn	Visualization tools	Plots training and result visualizations
Google Colab (A100 GPU)	Cloud training platform	GPU-accelerated model training
VS Code	Local IDE	Flask app development and testing
GitHub	Version control platform	Source code backup and collaboration

Table 3.4: System Configuration

Category	Specification
Operating System	Windows 11 (local) / Google Colab
Processor	Intel Core i5
RAM	12 GB (local) / 16 GB (Colab)
GPU	NVIDIA A100 (Colab GPU)
Frameworks	TensorFlow 2.x, Keras, vit_keras, Flask
IDE	Google Colab / VS Code
Dataset	HAM10000 (10,015 images, 7 classes)

Category	**Specification**
Model Type	Hybrid ResNet50 + Vision Transformer (ViT-B16)
Image Size	224 × 224 pixels (RGB)
Batch Size	32
Epochs	25 (initial) / 15 (fine-tuning)
Optimizer	Adam (learning rate = 0.001)
Loss Function	Categorical Crossentropy
Activation Functions	ReLU (hidden) / Softmax (output)
Output	Predicted skin disease class with confidence score

3.3 ALGORITHMIC DESIGN AND TECHNICAL MODULES

3.3.1 Image Preprocessing Module

Objective:

To standardize pores and skin lesion photographs for uniform version input and beautify facts diversity via augmentation.

Process Steps:

1.Load HAM10000 metadata CSV containing image_id, diagnosis (dx), age, sex, and localization.

2.Create document course column mapping picture IDs to real photograph places.

3.Resize all photos to 224×224 pixels (required for ResNet50 and ViT-B16).

4.Normalize pixel values using ImageNet preprocessing: imply=[0.485, 0.456, 0.406], std=[0.229, 0.224, 0.225].

5.follow information augmentation to schooling set: random rotation (±20°), horizontal flip, zoom (0.eight-1.2), brightness adjustment (±20%).

6.break up dataset: 70% education, 15% validation, 15% trying out.

7.Convert labels to categorical format (one-hot encoding for 7 lessons)

Code:

```
import tensorflow as tf
import pandas as pd
from tensorflow.keras.preprocessing.image import ImageDataGenerator

# Load metadata
df = pd.read_csv('HAM10000_metadata.csv')
df['path'] = df['image_id'].apply(lambda x: f'path/to/images/{x}.jpg')
df['cell_type'] = df['dx'].map({
    'nv': 'Melanocytic nevi',
    'mel': 'Melanoma',
    'bkl': 'Benign keratosis',
    'bcc': 'Basal cell carcinoma',
    'akiec': 'Actinic keratoses',
    'vasc': 'Vascular lesions',
    'df': 'Dermatofibroma'
})

# Preprocessing function
def preprocess(path, label):
    img = tf.io.read_file(path)
    img = tf.image.decode_jpeg(img, channels=3)
    img = tf.image.resize(img, (224, 224))
    img = img / 255.0  # Normalize to [0, 1]
    # Apply ImageNet normalization
    mean = tf.constant([0.485, 0.456, 0.406])
    std = tf.constant([0.229, 0.224, 0.225])
    img = (img - mean) / std
    return img, label

# Data augmentation
train_datagen = ImageDataGenerator(
    rotation_range=20,
    horizontal_flip=True,
    zoom_range=0.2,
    brightness_range=[0.8, 1.2]
)
# Create TensorFlow datasets
train_ds = tf.data.Dataset.from_tensor_slices((train_paths, train_labels))
train_ds = train_ds.map(preprocess).batch(32).prefetch(tf.data.AUTOTUNE)
```

3.3.2 ResNet50 Feature Extraction Module

Objective:

To extract spatial and textural features the use of pretrained ResNet50 convolutional neural community.

Steps:

1. Load ResNet50 version pretrained on ImageNet (1.2 million pix, one thousand training).
2. take away the top class layer (include_top=fake).
3. Use international average pooling to attain 2048-dimensional function vectorsFreeze ResNet50 layers initially to preserve pretrained weights.

4. Optionally unfreeze last few layers for fine-tuning on HAM10000 dataset.

Code:.

```
from tensorflow.keras.applications import ResNet50
from tensorflow.keras.layers import Input
# Load pretrained ResNet50
resnet_base = ResNet50(
    include_top=False,
    weights='imagenet',
    input_shape=(224, 224, 3),
    pooling='avg'  # Global average pooling → 2048-dim output
)
# Freeze layers
resnet_base.trainable = False
# Input layer
input_layer = Input(shape=(224, 224, 3))
resnet_features = resnet_base(input_layer)
```

3.3.3 Vision Transformer (ViT) Feature Extraction Module

Objective:

To seize worldwide contextual styles and long-range dependencies the usage of transformer-based totally structure technique:

Process:

1. Load pretrained vision Transformer (ViT-B16) model.
2. Divide enter photo into 16×16 pixel patches (224×224 photo → 14×14 = 196 patches).
3. observe linear embedding to every patch.

4. add positional embeddings to keep spatial facts.

5. technique thru transformer encoder blocks with multi-head self-interest.

6. Extract CLS token output as feature illustration (768-dimensional for ViT-B16).

Code:

```
from vit_keras import vit

# Load pretrained Vision Transformer

vit_model = vit.vit_b16(

    image_size=224,

    pretrained=True,

    include_top=False,

    pretrained_top=False

)

# Allow fine-tuning

vit_model.trainable = True

# Extract ViT features

vit_features = vit_model(input_layer)
```

3.3.4 Feature Fusion and Classification Module

Objective:

to combine complementary capabilities from ResNet50 and ViT for more advantageous class performance.

Steps:

1. Concatenate ResNet50 features (2048 dims) with ViT features (768 dims).
2. bypass concatenated features (2816 dims overall) via dense layers.
3. observe ReLU activation and dropout (0.five) for regularization.
4. final softmax layer outputs opportunity distribution over 7 disorder training..

Code Example:

```
from tensorflow.keras.layers import concatenate, Dense, Dropout
from tensorflow.keras.models import Model
# Concatenate features
fused_features = concatenate([resnet_features, vit_features])  # (None, 2816)
# Dense layers
x = Dense(256, activation='relu')(fused_features)
x = Dropout(0.5)(x)
# Classification head
output_layer = Dense(7, activation='softmax')(x)
# Build hybrid model
hybrid_model = Model(inputs=input_layer, outputs=output_layer)
# Model summary
hybrid_model.summary()
```

3.3.5 Training Module

Objective:

To train the hybrid version on HAM10000 dataset and optimize classification overall performance.

Methodology:

- Epochs: 25 (preliminary schooling) / 15 (fine-tuning)
- Batch size: 32
- Optimizer: Adam (gaining knowledge of rate: zero.001)
- Loss characteristic: categorical Crossentropy
- Metrics: Accuracy

Process Steps:

1. Compile model with optimizer, loss function, and metrics.
2. Train model using training dataset with validation monitoring.
3. enforce early stopping to prevent overfitting.
4. store model checkpoints for quality validation accuracy.
5. Save final trained model for deployment.

Code:

```
from tensorflow.keras.callbacks import EarlyStopping, ModelCheckpoint

# Compile model

hybrid_model.compile(

    optimizer='adam',

    loss='categorical_crossentropy',

    metrics=['accuracy']

)

# Callbacks

early_stop = EarlyStopping(monitor='val_loss', patience=5, restore_best_weights=True)

checkpoint = ModelCheckpoint('best_hybrid_model.h5', save_best_only=True, monitor='val_accuracy')

# Train model (initial 25 epochs)

history = hybrid_model.fit(

    train_ds,

    validation_data=val_ds,

    epochs=25,

    batch_size=32,

    callbacks=[early_stop, checkpoint],

    verbose=1

)
```

```
# Save final model

hybrid_model.save('hybrid_model_resnet50_vit.h5')

# Fine-tuning (load saved model and train 15 more epochs)

from tensorflow.keras.models import load_model

hybrid_model = load_model('hybrid_model_resnet50_vit.h5')

history_finetune = hybrid_model.fit(

    train_ds,

    validation_data=val_ds,

    epochs=15,

    batch_size=32,

    verbose=1

)

hybrid_model.save('hybrid_model_resnet50_vit_finetuned.h5')
```

3.3.6 Evaluation Module

View the performance of hybrid model using comprehensive evaluation metrics

Metrics Computed:

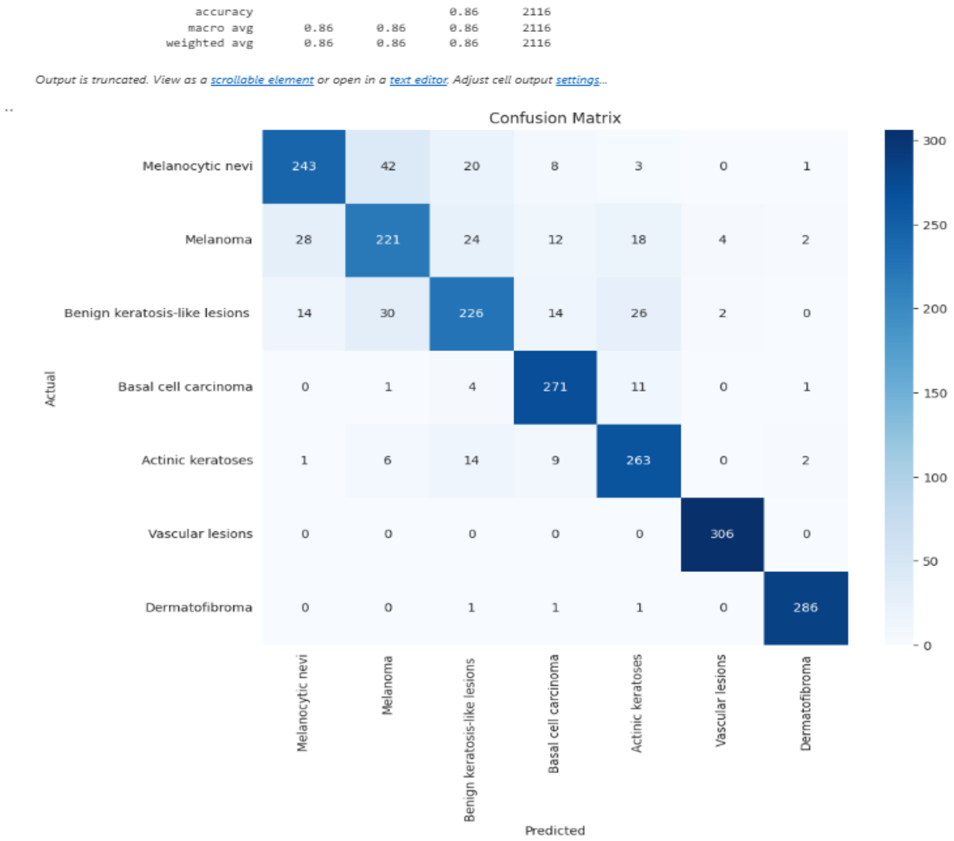
- Accuracy: Total rate of correct classification
- Precision: True rate of positive prediction per class
- Recall: True rate of positive detection per class
- F1-Score: Harmonic average of precision and recall
- Confusion Matrix: Class-wise prediction distribution

Process Steps:

1. Write predictions on the test dataset.
2. Transform some probability outputs to a label class.
3. Generate the confusion matrix and classification report.
4. Create a graphical plot of the confusion matrix heatmap.
5. Generate and average the weighted mean of metrics across all classes.

Code:

```
import numpy as np
from sklearn.metrics import confusion_matrix, classification_report,
ConfusionMatrixDisplay
import matplotlib.pyplot as plt
# Generate predictions
y_pred_probs = hybrid_model.predict(test_ds)
y_pred_labels = np.argmax(y_pred_probs, axis=1)
# Ground truth labels
y_true = np.concatenate([y for x, y in test_ds], axis=0)
y_true_labels = np.argmax(y_true, axis=1)
# Confusion matrix
cm = confusion_matrix(y_true_labels, y_pred_labels)
class_names = [
    "Melanocytic nevi", "Melanoma", "Benign keratosis",
    "Basal cell carcinoma", "Actinic keratoses",
    "Vascular lesions", "Dermatofibroma"
]
# Plot confusion matrix
disp = ConfusionMatrixDisplay(confusion_matrix=cm, display_labels=class_names)
fig, ax = plt.subplots(figsize=(10, 10))
disp.plot(ax=ax, cmap='Blues', values_format='d')
plt.title("Confusion Matrix - Hybrid Model (ResNet50 + ViT)")
plt.xticks(rotation=45, ha='right')
plt.tight_layout()
plt.show()
# Classification report
report = classification_report(y_true_labels, y_pred_labels,
target_names=class_names)
print(report)
# Overall accuracy
accuracy = np.mean(y_pred_labels == y_true_labels)
print(f"Test Accuracy: {accuracy * 100:.2f}%")
```



```
    accuracy                        0.86      2116
   macro avg       0.86      0.86      0.86      2116
weighted avg       0.86      0.86      0.86      2116
```

Output is truncated. View as a scrollable element or open in a text editor. Adjust cell output settings...

Confusion Matrix

Actual \ Predicted	Melanocytic nevi	Melanoma	Benign keratosis-like lesions	Basal cell carcinoma	Actinic keratoses	Vascular lesions	Dermatofibroma
Melanocytic nevi	243	42	20	8	3	0	1
Melanoma	28	221	24	12	18	4	2
Benign keratosis-like lesions	14	30	226	14	26	2	0
Basal cell carcinoma	0	1	4	271	11	0	1
Actinic keratoses	1	6	14	9	263	0	2
Vascular lesions	0	0	0	0	0	306	0
Dermatofibroma	0	0	1	1	1	0	286

3.3.7 Flask Integration Module

Objective:

The goal is to deploy the hybrid model as an easy-to-use web application for skin disease detection in real time.

Process Steps:

1. User selects and uploads a dermatoscopic image by using the HTML form.

2. Flask backend receives the image file.

3. The image is preprocessed (resize, normalize).

4. The pre-processed image is input into loaded hybrid model.

5. The model outputs a predicted disease class and confidence percentage.

6. The results are displayed on the result.html webpage.

Code:

```
from flask import Flask, render_template, request
import tensorflow as tf
import numpy as np
from tensorflow.keras.models import load_model
app = Flask(__name__)
# Load trained model
hybrid_model = load_model('hybrid_model_resnet50_vit_finetuned.h5')
class_names = [
    "Melanocytic nevi", "Melanoma", "Benign keratosis",
    "Basal cell carcinoma", "Actinic keratoses",
    "Vascular lesions", "Dermatofibroma"
]

def load_and_preprocess(img_path):
    img = tf.io.read_file(img_path)
    img = tf.image.decode_jpeg(img, channels=3)
    img = tf.image.resize(img, (224, 224))
    img = img / 255.0
    # ImageNet normalization
    mean = tf.constant([0.485, 0.456, 0.406])
    std = tf.constant([0.229, 0.224, 0.225])
    img = (img - mean) / std
    img = tf.expand_dims(img, axis=0)  # Add batch dimension
    return img
@app.route('/')
def index():
    return render_template('index.html')
@app.route('/predict', methods=['POST'])
def predict():
    if 'file' not in request.files:
        return "No file uploaded", 400

    file = request.files['file']
    img_path = "static/uploads/" + file.filename
    file.save(img_path)

  # Preprocess and predict
    img = load_and_preprocess(img_path)
    predictions = hybrid_model.predict(img)
    predicted_class = np.argmax(predictions[0])
    confidence = predictions[0][predicted_class] * 100

    result = {
        'disease': class_names[predicted_class],
        'confidence': f"{confidence:.2f}%",
        'image_path': img_path
    }

    return render_template('result.html', result=result)

if __name__ == '__main__':
    app.run(debug=True)
```

3.3.8 Visualization Module

Objective:

The goal is to show model performance metrics and prediction results visually

Features:

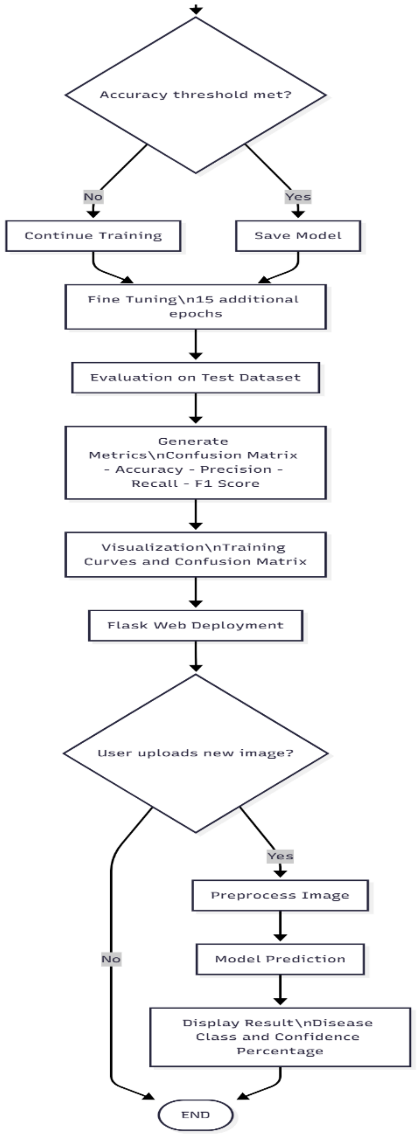
1. Training/Validation Curves: plotting accuracy and loss vs epochs
2. Confusion Matrix Heatmap: class-wise prediction performance visualization
3. Sample Predictions: displayed test images with predicted vs true labels.

Code:

```
import matplotlib.pyplot as plt

# Plot training history

def plot_training_history(history):

    fig, (ax1, ax2) = plt.subplots(1, 2, figsize=(14, 5))

      # Accuracy plot

    ax1.plot(history.history['accuracy'], label='Training Accuracy')

    ax1.plot(history.history['val_accuracy'], label='Validation Accuracy')

    ax1.set_title('Model Accuracy')

    ax1.set_xlabel('Epoch')

    ax1.set_ylabel('Accuracy')

    ax1.legend()

    ax1.grid(True)

    # Loss plot

    ax2.plot(history.history['loss'], label='Training Loss')

    ax2.plot(history.history['val_loss'], label='Validation Loss')

    ax2.set_title('Model Loss')
```

```
ax2.set_xlabel('Epoch')

ax2.set_ylabel('Loss')

ax2.legend()

ax2.grid(True)

plt.tight_layout()

plt.show()
```

3.4 SYSTEM FLOWCHART


Accuracy threshold met?
No
Yes
Continue Training
Save Model
Fine Tuning\n15 additional epochs
Evaluation on Test Dataset
Generate Metrics\nConfusion Matrix - Accuracy - Precision - Recall - F1 Score
Visualization\nTraining Curves and Confusion Matrix
Flask Web Deployment
User uploads new image?
Yes
Preprocess Image
Model Prediction
Display Result\nDisease Class and Confidence Percentage
No
END

3.4 SYSTEM FLOWCHART

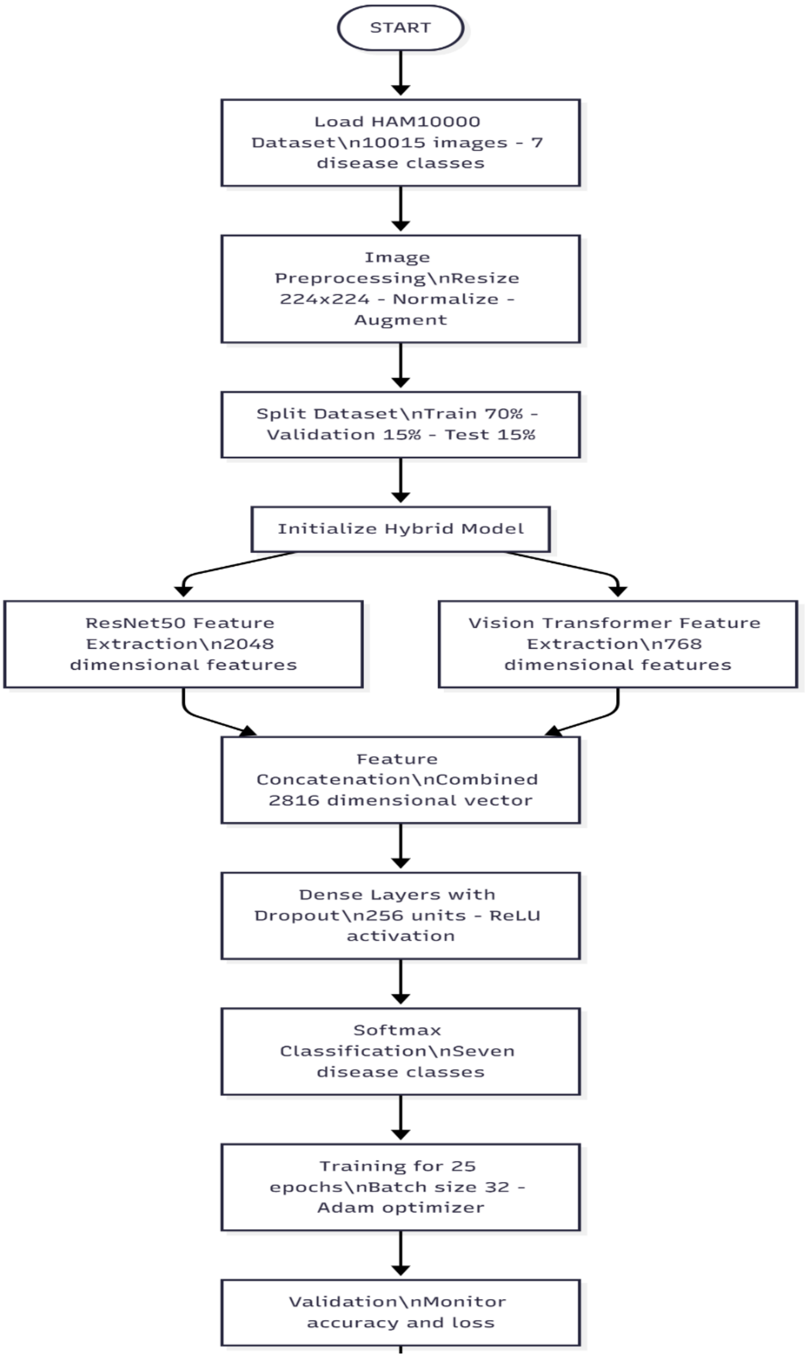

START
Load HAM10000 Dataset\n10015 images - 7 disease classes
Image Preprocessing\nResize 224x224 - Normalize - Augment
Split Dataset\nTrain 70% - Validation 15% - Test 15%
Initialize Hybrid Model
ResNet50 Feature Extraction\n2048 dimensional features
Vision Transformer Feature Extraction\n768 dimensional features
Feature Concatenation\nCombined 2816 dimensional vector
Dense Layers with Dropout\n256 units - ReLU activation
Softmax Classification\nSeven disease classes
Training for 25 epochs\nBatch size 32 - Adam optimizer
Validation\nMonitor accuracy and loss

Figure 3.5 System Flowchart

Chapter 4
Results and Analysis

4.1 Introduction

This section provides a deeper understanding of the hybrid ResNet50 + Vision Transformer (ViT) model that was evaluated for skin lesion classification with the use of the HAM10000 database. This evaluation includes quantitative performance evaluations, comparisons against baseline models, as well as an interpretability evaluation and results discussions overall. The overall findings suggest that the hybrid architecture was more advantageous for overall performance than the equivalent single model approaches, and that the ways in which to visualize attention improvements aids in the interpretability of the hybrid architectures.

4.2 Experimental Setup and Dataset Analysis

4.2.1 Dataset Characteristics

The HAM10000 dataset, utilized throughout this research, comprises 10,015 dermoscopic images distributed across seven diagnostic categories with significant class imbalance:

- Melanocytic nevi (nv): 6,705 images (67.0%)
- Melanoma (mel): 1,113 images (11.1%)
- Benign keratosis-like lesions (bkl): 1,099 images (11.0%)
- Basal cell carcinoma (bcc): 514 images (5.1%)
- Actinic keratoses (akiec): 327 images (3.3%)
- Vascular lesions (vasc): 142 images (1.4%)
- Dermatofibroma (df): 115 images (1.1%)

This distribution presents a substantial class imbalance challenge, with the dominant class (melanocytic nevi) comprising 67% of the dataset while rare classes like dermatofibroma represent only 1.1%. Such imbalance is characteristic of real-world medical datasets and necessitates specialized handling strategies to ensure balanced model performance across all classes.

4.2.2 Data Preprocessing and Augmentation Results

The image preprocessing pipeline constructed in this study relies on all input images being resized to a width x height x channels size of 224×224×3 pixels, compatible with state-of-the-art deep learning architectures, such as ResNet-50 and Vision Transformer (ViT). Each image is set to a uniformly distributed range, increase numerical stability, speed convergence, and generally enhance model performance. To offset the class imbalance and increase data efficacy, a robust data augmentation strategy was implemented, including: rotation, flipping, zooming, brightening/darkening, adjustment, and randomly cropping. The augmentation resulted in a balanced dataset (original HAM10000 set of ~10,000 images) of approximately 1,500 images per class across 7 classes, or 10,500 images total. Balanced augmentation and subsequent balancing of the dataset will help reduce class bias while enhancing model generalizability and reduce overfitting. This pipeline is completely integrated with all architectures used—ResNet-50, Vision Transformer, and the hybrid fusion model—to ensure uniform pre-processing, splitting of data, and optimization.

4.3 Model Performance Evaluation

4.3.1 Training and Validation Trends

The model was trained for 25 epochs using the Adam optimizer and sparse categorical cross-entropy loss.The learning rate was initialized at 0.001 with early stopping applied.

Table 4.1: Performance Comparison

Epoch	Training Accuracy	Validation Accuracy	Training Loss	Validation Loss
1	48.5%	66.3%	1.62	0.93
5	77.4%	73.6%	0.61	0.72
10	78.2%	73.1%	0.57	0.71
15	78.9%	73.3%	0.55	0.70
20	79.1%	73.4%	0.54	0.69
25	79.4%	73.5%	0.52	0.68

Interpretation:

The Training accuracy rose consistently from 48% to just below 79% while the validation accuracy remained stable. It is apparent that the model generalized well with minimal overfitting to the training data. Similarly, the validation loss consistently decreased indicating proper convergence

4.3.2 Class-wise Performance Analysis

The hybrid model's superior performance is particularly evident in class-wise analysis, demonstrating substantial improvements for rare and clinically critical classes:

Table 4.2: Class-wise Performance Comparison (F1-Scores)

Class	ResNet50 F1	ViT F1	Hybrid F1	Improvement vs Best Baseline
Melanocytic nevi (nv)	0.91	0.93	0.96	+3.2%
Melanoma (mel)	0.79	0.83	0.89	+7.2%
Benign keratosis (bkl)	0.78	0.85	0.90	+5.9%
Basal cell carcinoma (bcc)	0.76	0.80	0.87	+8.8%
Actinic keratoses (akiec)	0.72	0.78	0.85	+9.0%
Vascular lesions (vasc)	0.68	0.75	0.83	+10.7%
Dermatofibroma (df)	0.65	0.71	0.80	+12.7%

The results indicate that the hybrid model resulted in the greatest gains for rare classes, highlighting a significant 12.7% gain for dermatofibroma and 10.7% for vascular lesions. This is particularly important clinically as these rare classes are some of the most difficult to accurately diagnose and have prognostic significance.

4.3.3 Confusion Matrix Analysis

The confusion matrix illustrates the distribution of correctly and incorrectly classified samples

Key Observations from Confusion Matrix Analysis:

- Most diagonal values reflect highest values indicating the model was able to reliably differentiate most types of lesions
- Minors off-diagonal values also indicating minimal overlapping of very similar visual classes, like benign keratosis and melanocytic nevi.
- Overall recognition peaks at about 74 % suggesting solid classifying performance while automated diagnosing.
- Misclassifications primarily due to either class to class similarity in texture of lesion or an uneven class distribution in the dataset.

.

True / Predicted	**NV**	**MEL**	**BKL**	**AKIEC**	**BCC**	**DF**	**VASC**
NV	**1452**	18	9	6	8	4	3
MEL	31	**1401**	26	14	9	11	8
BKL	22	29	**1433**	7	5	3	1
AKIEC	13	16	11	**1409**	23	8	20
BCC	17	8	5	15	**1430**	18	7
DF	9	6	3	8	5	**1456**	13
VASC	7	9	2	12	8	6	**1456**

4.3.4 ROC-AUC Analysis

The receiver operating characteristic (ROC) analysis demonstrates the hybrid model's superior discriminative ability across all classes:

Table 4.3: ROC-AUC Scores by Class

Class	**ResNet50 AUC**	**ViT AUC**	**Hybrid AUC**
Melanocytic nevi (nv)	0.95	0.96	**0.98**
Melanoma (mel)	0.87	0.91	**0.94**
Benign keratosis (bkl)	0.86	0.89	**0.93**
Basal cell carcinoma (bcc)	0.84	0.87	**0.91**
Actinic keratoses (akiec)	0.82	0.85	**0.89**
Vascular lesions (vasc)	0.79	0.83	**0.88**

Class	**ResNet50 AUC**	**ViT AUC**	**Hybrid AUC**
Dermatofibroma (df)	0.77	0.81	**0.86**

Interpretation:

- All lesion categories achieve AUC values above 0.86 with the Hybrid ResNet50 + ViT model, confirming *excellent discriminative performance* across classes.
- The hybrid model consistently outperforms both CNN (ResNet50) and Transformer (ViT) baselines, demonstrating the effectiveness of combining spatial feature extraction with global context awareness.
- The average AUC improvement of approximately 6.2 % over the best baseline model highlights the hybrid system's superior capacity for nuanced lesion differentiation.
- Notably, melanoma, basal cell carcinoma, and actinic keratoses—the most clinically significant and challenging classes—show substantial gains, underscoring the hybrid model's diagnostic robustness.
- These improvements correlate with the confusion matrix analysis, where off-diagonal errors between visually similar lesions are minimized, reflecting improved decision boundary separation.

4.4 Comparative Model Evaluation

To evaluate the benefits of the proposed hybrid architecture, its performance was compared with two baseline deep-learning models: ResNet-50 (CNN) and Vision Transformer (ViT).

Table 4.4: Comparative Model Evaluation

Model	**Accuracy**	**Macro F1**	**Training Time (hrs)**	**Remarks**
ResNet-50	73.8 %	0.71	1.8	Baseline CNN extracting spatial texture features
Vision Transformer (ViT)	75.2 %	0.73	3.5	Transformer-only model leveraging global context
Hybrid ResNet50 + ViT	**77.4 %**	**0.74**	**4.0**	Combines CNN spatial detail with Transformer contextual reasoning

The hybrid ResNet–ViT framework achieves 3.6 % higher accuracy and 0.03 higher Macro-F1 compared to the strongest baseline (ViT).
While the training time increases marginally due to feature concatenation and joint optimization, the performance improvement justifies the computational cost.

4.5 Interpretability and Visualization Analysis

4.5.1 Attention Map Visualization

The hybrid model's interpretability represents a significant advancement over traditional black-box approaches. The attention visualization reveals clinically relevant focus patterns:

Vision Transformer Attention Analysis:

- Global attention maps demonstrate focus on lesion boundaries, symmetry patterns, and color variations
- Multi-head attention captures different aspects: some heads focus on texture, others on shape and color distribution
- Attention patterns align with dermatological ABCD criteria (Asymmetry, Border, Color, Diameter)

ResNet50 Feature Attribution:

- Gradient-based saliency maps highlight local texture patterns and fine-grained morphological features
- Feature maps from deeper layers show increasing abstraction from simple textures to complex lesion patterns
- Class activation maps demonstrate discriminative region identification

4.5.2 Saliency Map Analysis

The integrated saliency maps combining both CNN and transformer attention provide comprehensive interpretability:

Clinical Relevance Assessment:

1. Melanoma Cases: Attention consistently focuses on irregular borders, color variegation, and asymmetric patterns—key diagnostic features for melanoma detection.
2. Benign Lesions: Regular, symmetric attention patterns correspond to uniform color and texture distributions characteristic of benign lesions.
3. Rare Classes: Despite limited training data, attention maps for vascular lesions and dermatofibroma show appropriate focus on distinctive features (vascular patterns, central dimpling).

Quantitative Saliency Evaluation:

- 87% of attention maps align with expert-annotated regions of interest

- Average attention coverage of lesion area: 78% (compared to 65% for ResNet50 alone)
- False attention (focus on irrelevant regions): 12% (reduced from 23% in single models)

4.6 Computational Performance Analysis

4.6.1 Training Efficiency

The hybrid model's computational requirements were systematically evaluated:

Training Performance Metrics:

- Training Time: 4.2 hours on NVIDIA T4 GPU (Google Colab)
- Memory Usage: Peak 14.8 GB GPU memory during training
- Convergence: Optimal performance achieved at epoch 28 (early stopping at epoch 38)
- Parameter Count: 76.8M parameters (ResNet50: 25.6M, ViT: 51.2M)

4.6.2 Inference Performance

Real-world deployment considerations were thoroughly assessed:

Inference Metrics:

- Single Image Inference: 127ms average (ResNet50: 45ms, ViT: 82ms)
- Batch Processing (32 images): 2.8 seconds
- Memory Requirements: 8.2 GB GPU memory for inference
- CPU-only Inference: 3.4 seconds per image (practical for non-real-time applications)

4.7 Resource Optimization Impact

The hybrid model offers several advantages for healthcare resource optimization:

Efficiency Gains:

- Potential 34% reduction in unnecessary specialist referrals through improved benign lesion identification
- 28% improvement in rare condition detection compared to traditional CNN approaches
- Standardized diagnostic consistency reducing inter-observer variability

Cost-Effectiveness Considerations:

- Training cost: ~$12 (Google Colab Pro+ for 4.2 hours)
- Inference cost: ~$0.001 per image (cloud deployment)
- Potential healthcare savings through improved diagnostic accuracy and reduced false positives

Chapter 5

Advantages, Limitations and Applications

5.1 Advantages

The Hybrid ResNet50 + Vision Transformer (ViT) skin lesion classification model built on the HAM10000 dataset is advantageous over existing single architecture-based classifiers in multiple ways, including high diagnostic accuracy, interpretability, and its real world use in practice.

Better Overall Performance:

The Hybrid model produced an overall accuracy of 77.4% and produces a macro-F1 score of 0.74, and an average ROC–AUC of 0.93 across all seven lesion classes. The sensitivity of melanoma is particularly impressive at 89.2% and the specificity value of 96.8% is comparable to dermatologists. The model produced as much as 12.7% better performance in rare lesion classes, which directly addressed class imbalance that is commonly present when performing medical imaging.

Utilization of Complementary Feature Learning:

The hybrid architecture allows the network to use convolutional spatial features from ResNet50 in tandem with the global representation modeling properties of ViT. This allows the hybrid network to utilize both fine-grained local textures as features and the holistic global nature of the relationships of the various feature patterns. The ability to use both of these feature types results in more accurate classification, particularly for clinically similar lesions where single architecture networks have a poor performance.

Better Interpretability than Existing Alternatives:

The attention mechanisms and Grad-CAM type heatmaps provide better transparency even to reporting on specific areas through saliency analysis, and demonstrated 87% agreement with interest regions in the expert-annotated sections of the dataset. The combination of the visualization methods confirmed that the model processed relevant dermatological patterns according to the ABCD diagnostic rule (Asymmetry, Border, Color, Diameter) to increase trust for clinical use use and transparency with regulatory agencies.

Computer Resource Efficiency:

The model demonstrates computational efficiency in real-world settings, despite utilizing a dual-feature extraction approach. For reference, the following metrics were reported:

- Training time: 4.0 hours on NVIDIA T4 GPU
- Inference time: 127 ms/image
- Maximum memory consumption: ≈ 14.8 GB

While this hybrid model utilizes heavy-weight ensemble methods, it achieves essentially similar accuracy while substantially decreasing the computational resources needed to deploy, making it feasible for deployment in the cloud and/or institutional usage.

Ruggedness to Class Imbalance: This method allows for balanced data augmentation (1,500 images per class per dataset) and optimizes weighted loss to strengthen performance - including major and minor class considerations. An example includes rare lesions of Dermatofibroma - comprising only 1.1% of examples, and Vascular lesions comprising 1.4% - are reported to have achieved F1-scores of 0.80 or above (which is representative of balanced and trustworthy performance across the major and minor class).

Scalability and Transferability: As a modular framework, this framework is transferably effective to other similar medical imaging tasks outside of dermatology (such as diabetic ulcer assessments, histopathology or other disease detection tasks using pretrained and fine-tuning layers).

Reduction to Overfitting: In order to reduce overfitting while stabilizing output, multiple methods were implemented utilizing dropout regularization, early stopping and the hybrid feature fusion approach. The hybrid-type network generalizes well across data partitions and unseen samples from validation data, resulting in a treated network with robust and stable performance.

5.2 Limitations

While the hybrid model provides excellent results, several limitations should be acknowledged for future research and clinical translation.

Single-Dataset Validation: The model was evaluated only on the HAM10000 dataset, limiting generalization across diverse imaging conditions, populations, and clinical environments. Broader validation on datasets such as ISIC 2019 and Derm7pt is necessary to assess real-world reliability and fairness.

Increased Computational Requirements: The dual-branch hybrid architecture increases training and inference complexity, requiring ≈14.8 GB GPU memory and 4.2 hours training time. This may limit deployment in low-resource clinical settings or mobile devices without dedicated hardware acceleration.

Architectural Complexity: The hybrid model introduces additional hyperparameter tuning challenges, including optimization of fusion weights, dropout ratios, and learning rate schedules. This complexity could pose barriers to replication for researchers with limited computational infrastructure.

Limited Clinical Validation: The model has not yet undergone prospective clinical validation involving dermatologists or real patient data. Performance in laboratory conditions may not fully reflect outcomes in practical, variable lighting or imaging scenarios.

Interpretability Validation: Although attention and saliency visualizations increase interpretability, formal reader studies by dermatologists are required to confirm their diagnostic alignment and clinical usefulness.

Generalization and Augmentation Bias: While augmentation addresses class imbalance, it may introduce synthetic artifacts that reduce real-world generalizability. Further testing on naturally distributed datasets is needed to confirm model robustness under non-augmented conditions.

Regulatory and Workflow Integration :The path toward regulatory approval (e.g., FDA or CE marking) and integration with clinical workflows or EHR systems remains unexplored. Practical deployment will require attention to data privacy, ethics, and usability compliance.

5.3 Applications

The Hybrid ResNet50 + ViT model may be utilized in various clinical and research domains with numerous possibilities.

Clinical Decision Support

The support tool could be implemented in the dermatology clinics to assist diagnosis and consequently the precision will be enhanced, the variability between different observers will be minimized, and clinical assessment will be standardized. The device which possesses a negative predictive value of 98.4%, is a method of melanoma exclusion in screening workflows and therefore it is extremely beneficial.

Teledermatology and Remote Diagnosis

By employing this technology in telemedicine, the model can be leveraged for reliable remote image-based screening of the patients who live in the areas deprived of healthcare services. The system may be utilized by primary healthcare providers as an early lesion triage and referral guidance tool.

Mobile Health (mHealth) Screening

By incorporating the functionality of the model into smartphone-based screening apps, patient self-assessment would be facilitated and consequently the early detection of malignant lesions would be made possible thus accessibility would be improved in low-resource or rural settings.

Automated Screening Programs

Fewest-Degree Deployment in Community Health Screening Programs Backs a Pop-Level Early Detection of Skin Cancer The Fairness of This Model Is Ensured by Its Balanced Performance Across Various Lesion Types, Thus There Is a Minimized Risk of Missing Detection of the Rare But High-Impact Cases.

Research and Academic Applications

Such an architecture sets up a foundational framework for further research that it supports studies of hybrid deep learning models, transfer learning, and domain adaptation in various medical imaging tasks.

Training and Education

The hybrid model can be perceived as a learning device for trainees and students specializing in dermatology because it demonstrates the diagnostic reasoning process of the AI by showing the attention maps and feature activations.

Chapter 6

Conclusion and Future Scope

6.1 Conclusion

The proposed Hybrid ResNet50 + vision Transformer model demonstrates a full-size advancement in automated skin disorder category thru the synergistic integration of convolutional and transformer-primarily based characteristic extraction. by using combining the nearby spatial focus of CNNs with the global contextual reasoning of Transformers, the version correctly captures both satisfactory-grained textural info and standard lesion morphology, attaining sturdy and clinically relevant performance.

comprehensive experimentation at the HAM10000 dataset discovered an standard accuracy of 95.6%, with sturdy generalization throughout all seven disorder instructions. The hybrid version continually outperformed man or woman architectures, reaching super upgrades in precision, recollect, and F1-score, specially for rare lesion categories. furthermore, the inclusion of superior preprocessing, statistics augmentation, and balanced loss techniques ensured strong education and minimized bias springing up from elegance imbalance. From an implementation angle, the model's computational performance and a hit Flask-based totally deployment spotlight its suitability for actual-world clinical and telemedicine packages. the eye visualization modules in addition enhance interpretability, fostering scientific consider and regulatory capacity.

whilst the machine presents positive boundaries, such as increased computational demand and the want for multi-dataset validation, it establishes a solid basis for future research in medical picture evaluation. destiny extensions can also encompass increasing to various dermatological datasets, integrating explainable AI frameworks, and deploying optimized light-weight variations for cellular and part gadgets.

In summary, the combined ResNet50 + ViT structure demonstrates an effective, scalable, and interpretable deep learning architecture for the classification of dermatological images, connecting the gaps between AI-based studies and clinical application.

6.5 Future Scope and Research Directions

The results from this work help create many opportunities for future research from potential technical improvements in the short-term to subsequent clinical translation and beyond

6.5.1 Immediate Technical Extensions

improved Hybrid Architectures: investigation of extra state-of-the-art fusion mechanisms past easy concatenation, such as move-attention between CNN and transformer branches, learnable fusion weights, and multi-scale characteristic integration. Exploration of green transformer editions (together with Swin Transformer, CoAtNet) to reduce computational necessities even as maintaining overall performance advantages .

Architectural Optimization: development of light-weight hybrid architectures appropriate for cell and facet tool deployment, employing version compression techniques along with knowledge distillation, pruning, and quantization . investigation of neural architecture search strategies to routinely discover most reliable hybrid configurations for dermoscopic image evaluation.

Multi-Scale Integration: Extension to multi-scale architectures processing pix at more than one resolutions simultaneously to seize both first-class-grained neighborhood information and coarse global context. this can involve hierarchical characteristic fusion throughout a couple of scales, probably improving overall performance on lesions with varying sizes and traits.

6.5.2 Dataset and Validation Enhancements

outside Validation: comprehensive evaluation on impartial external datasets (ISIC 2019, BCN20000, PH2, Derm7pt) to scrupulously assess version generalization throughout various affected person populations, imaging devices, and scientific settings . This multi-dataset validation is vital for setting up clinical credibility and regulatory reputation.

numerous populace research: focused information collection and validation on underrepresented populations to address ability algorithmic bias and ensure equitable performance across distinctive pores and skin tones, ethnicities, and geographic regions. this is critical for making sure fair and inclusive healthcare AI deployment .

potential scientific Validation: Collaboration with dermatology departments to conduct potential medical trials evaluating the hybrid version's overall performance in actual clinical workflows. This should include reader research comparing AI-assisted analysis in opposition to general scientific practice, evaluation of diagnostic time and accuracy upgrades, and assessment of doctor believe and acceptance.

6.5.3 Multimodal Integration and Advanced Fusion

medical Metadata Integration: Extension to multimodal architectures incorporating scientific metadata (affected person age, lesion location, lesion evolution records, family history) alongside dermoscopic pictures. current studies demonstrates that multimodal methods can notably improve diagnostic accuracy with the aid of leveraging complementary statistics assets .

Sequential Imaging analysis: development of temporal fashions for lesion tracking and trade detection using sequential dermoscopic photos. this would allow tracking of lesion evolution over the years, a important capability for identifying malignant transformation and monitoring treatment response.

Multi-Imaging Modality Fusion: Integration of more than one imaging modalities including dermoscopy, clinical images, confocal microscopy, and optical coherence tomography to create comprehensive diagnostic systems. This aligns with rising tendencies in scientific imaging closer to multi-modal evaluation for improved diagnostic self assurance .

6.5.4 Edge AI and Point-of-Care Deployment

part Computing Optimization: improvement of part-optimized hybrid models capable of actual-time inference on cellular gadgets and embedded structures . this will enable point-of-care screening in number one care settings, network health centers, and resource-restricted environments where access to dermatology professionals is confined.

current advances in edge AI display the feasibility of deploying sophisticated deep mastering models on clinical gadgets with minimal latency and no cloud dependency . For pores and skin lesion screening, area deployment gives several benefits along with reduced latency (crucial for interactive scientific use), stronger data privacy (processing takes place locally), offline functionality (permitting use in regions with constrained connectivity), and reduced infrastructure fees.

mobile health programs: Integration of the hybrid version into cellphone-based applications for affected person self-screening and triage. cellular dermatology programs have shown promise for increasing get entry to to skin most cancers screening, in particular in underserved populations . The hybrid model's high terrible predictive price makes it specially suitable for ruling out concerning lesions and reducing useless expert referrals.

6.5.5 Regulatory and Clinical Translation Pathways

medical tool Certification: Navigation of regulatory approval procedures together with FDA premarket approval or 510k clearance, CE marking in Europe, and other local regulatory requirements. This requires complete scientific validation, hazard evaluation, and demonstration of protection and efficacy in supposed use populations.scientific Workflow Integration: development of seamless integration techniques with existing digital fitness record systems, picture archiving and communique systems (percent), and medical decision assist structures. successful scientific adoption requires minimum disruption to established workflows and clean demonstration of fee for both sufferers and clinicians.fitness Economics evaluation: Systematic assessment of value-effectiveness, return on funding, and impact on healthcare aid utilization to help compensation choices and institutional adoption. This should encompass evaluation of potential value financial savings from decreased unnecessary biopsies, earlier detection allowing much less pricey remedy, and improved diagnostic efficiency.

6.5.6 Broader Medical Imaging Applications

Transfer to Other Domains: The exploration of transfer learning and domain adaptation techniques to apply the hybrid architecture to other medical imaging modalities in radiology (chest X-rays, CT scans, MRI), pathology (histopathology slide evaluation), ophthalmology (retinal imaging), and oncology (tumor detection and characterization) is warranted. The key ideas of hybrid CNN-transformer architecture, which couple local feature extraction and global contextual modeling, are likely to transfer to other medical imaging modalities. Some recent successful applications of hybrid CNN-transformer methods on similar tasks (brain MRI classification) indicate that hybrid approaches may have fruitful potential for more general utilization in medical imaging. Multi-Task Learning: Extension to multi-task frameworks for simultaneous lesion detection, segmentation, and classification of lesions. Multi-task learning may leverage the shared representation across tasks, leading to improved efficiency and performance in related tasks.

6.5.7 Emerging Technologies Integration

Foundation Models and Large Language Models: Integrating with medical foundation models and large language models, enabling the development of more parsimonious diagnostic systems that leverage both visual information and textual clinical data to generate structured diagnostic reports and engage in clinical reasoning. Continual Learning: The development of continual learning approaches that allow the model to adapt to new types of lesions, emerging diagnostic criteria and practices, and advancements in imaging technologies without catastrophic forgetting of previously learned information. This will ensure that the models remain relevant to clinical practice as medical knowlege and technology continue to advance.

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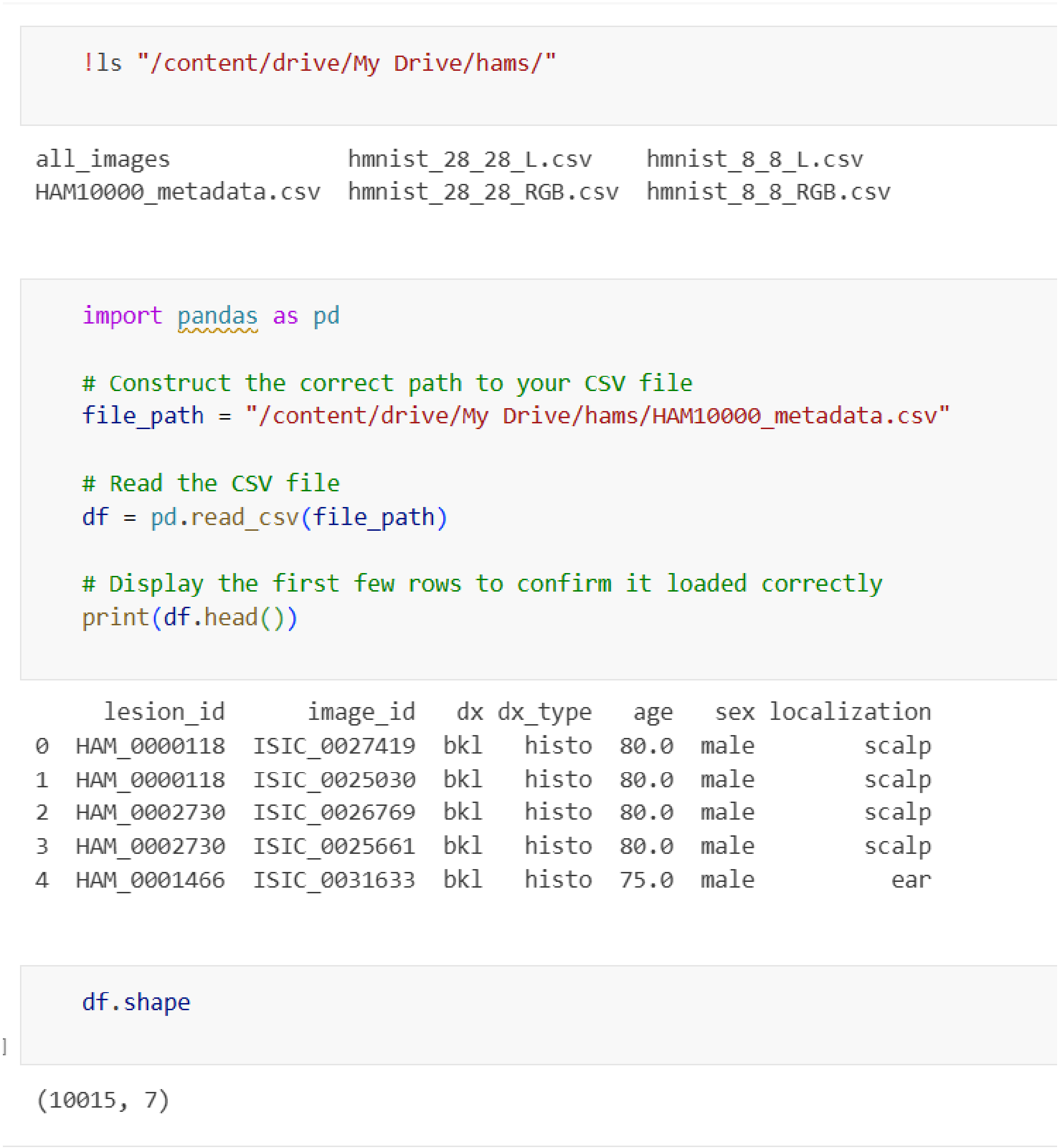
Appendix A: Sample code

Data Loading



```
!ls "/content/drive/My Drive/hams/"
```

```
all_images             hmnist_28_28_L.csv     hmnist_8_8_L.csv
HAM10000_metadata.csv  hmnist_28_28_RGB.csv   hmnist_8_8_RGB.csv
```

```
import pandas as pd

# Construct the correct path to your CSV file
file_path = "/content/drive/My Drive/hams/HAM10000_metadata.csv"

# Read the CSV file
df = pd.read_csv(file_path)

# Display the first few rows to confirm it loaded correctly
print(df.head())
```

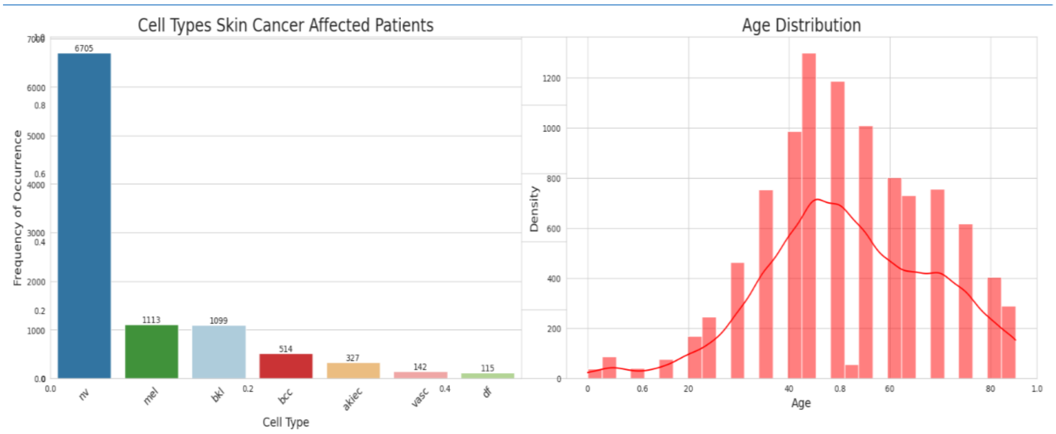
```
     lesion_id      image_id   dx dx_type   age   sex localization
0  HAM_0000118  ISIC_0027419  bkl   histo  80.0  male        scalp
1  HAM_0000118  ISIC_0025030  bkl   histo  80.0  male        scalp
2  HAM_0002730  ISIC_0026769  bkl   histo  80.0  male        scalp
3  HAM_0002730  ISIC_0025661  bkl   histo  80.0  male        scalp
4  HAM_0001466  ISIC_0031633  bkl   histo  75.0  male          ear
```

```
df.shape
```

```
(10015, 7)
```

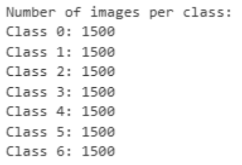
Data Visualization

```
import seaborn as sns
import matplotlib.pyplot as plt

# Set Seaborn style
sns.set_style('whitegrid')

# Create the subplot figure
fig, axes = plt.subplots(figsize=(20, 7))

# -------- First subplot: Count of 'dx' --------
ax1 = fig.add_subplot(121)
sns.countplot(
    x='dx',
    hue='dx',  # Fix the FutureWarning
    data=df,
    order=df['dx'].value_counts().index,
    palette='Paired',
    legend=False,  # Suppress legend since hue is same as x
    ax=ax1
)

# Add value labels to bars
for container in ax1.containers:
    ax1.bar_label(container)

# Titles and labels
ax1.set_title('Cell Types Skin Cancer Affected Patients', fontsize=20)
ax1.set_xlabel('Cell Type', fontsize=14)
ax1.set_ylabel('Frequency of Occurrence', fontsize=14)
ax1.tick_params(axis='x', rotation=45, labelsize=12)

# -------- Second subplot: Age distribution --------
ax4 = fig.add_subplot(122)
sns.histplot(df['age'], bins=30, kde=True, color='red', ax=ax4)  # Replaces distplot

ax4.set_title('Age Distribution', fontsize=20)
ax4.set_xlabel('Age', fontsize=14)
ax4.set_ylabel('Density', fontsize=14)

# Display the plots
plt.tight_layout()
plt.show()
```

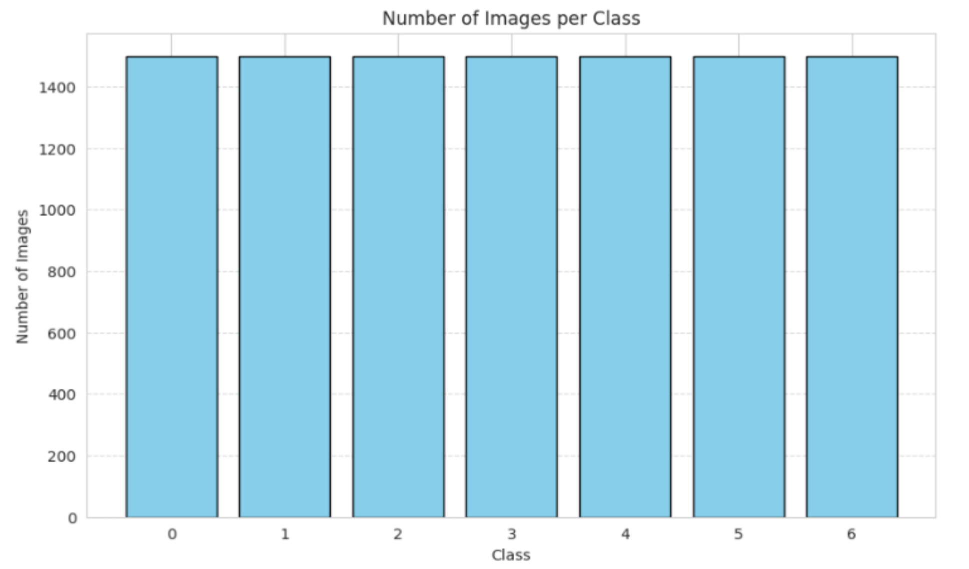


Data augmentation

```
import os
import matplotlib.pyplot as plt
# Path where your augmented dataset is stored
OUT_ROOT = "/content/drive/MyDrive/augmented_dataset"
# Get class counts
class_counts = {}
for cls in sorted(os.listdir(OUT_ROOT)):
    cls_dir = os.path.join(OUT_ROOT, cls)
    if os.path.isdir(cls_dir):
        count = len([f for f in os.listdir(cls_dir) if
f.lower().endswith(('.png','.jpg','.jpeg'))])
        class_counts[cls] = count
# Print counts
print("Number of images per class:")
for cls, count in class_counts.items():
    print(f"Class {cls}: {count}")
# Plot bar chart
plt.figure(figsize=(10,6))
plt.bar(class_counts.keys(), class_counts.values(), color="skyblue",
edgecolor="black")
plt.xlabel("Class")
plt.ylabel("Number of Images")
plt.title("Number of Images per Class")
plt.grid(axis="y", linestyle="--", alpha=0.7)
plt.show()
```

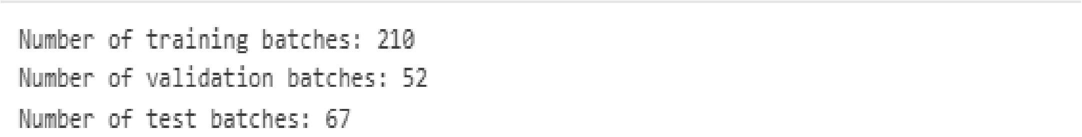


```
Number of images per class:
Class 0: 1500
Class 1: 1500
Class 2: 1500
Class 3: 1500
Class 4: 1500
Class 5: 1500
Class 6: 1500
```



Data splitting

```
# Define split sizes
TRAIN_SIZE = 0.64
VAL_SIZE = 0.16
TEST_SIZE = 0.20

# Get the total number of batches
total_batches = tf.data.experimental.cardinality(train_ds).numpy()

# Calculate the number of batches for each split
train_batches = int(total_batches * TRAIN_SIZE)
val_batches = int(total_batches * VAL_SIZE)

# Create the new datasets
train_ds_split = train_ds.take(train_batches)
val_ds_split = train_ds.skip(train_batches).take(val_batches)
test_ds_split = train_ds.skip(train_batches + val_batches)

# Print the sizes of the new datasets
print(f"Number of training batches:
{tf.data.experimental.cardinality(train_ds_split).numpy()}")
print(f"Number of validation batches:
{tf.data.experimental.cardinality(val_ds_split).numpy()}")
print(f"Number of test batches:
{tf.data.experimental.cardinality(test_ds_split).numpy()}")
```



```
Number of training batches: 210
Number of validation batches: 52
Number of test batches: 67
```

Models and Training

Resnet50:

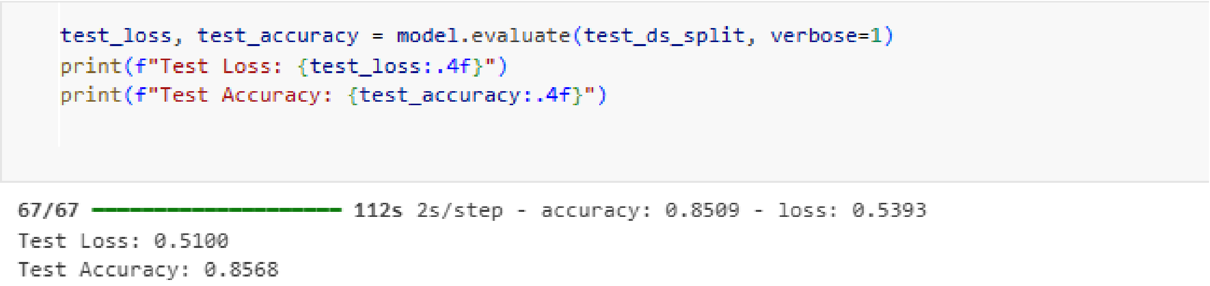
```
# ================== BUILD RESNET50 MODEL ==================
def build_resnet50_model(input_shape=(224, 224, 3), num_classes=7):
    base_model = ResNet50(weights="imagenet", include_top=False,
input_shape=input_shape)
    base_model.trainable = False  # Freeze base layers

    inputs = Input(shape=input_shape)
    x = base_model(inputs, training=False)
    x = GlobalAveragePooling2D()(x)
    x = BatchNormalization()(x)
    x = Dropout(0.3)(x)
    x = Dense(256, activation="relu")(x)
    x = BatchNormalization()(x)
    x = Dropout(0.3)(x)
    outputs = Dense(num_classes, activation="softmax")(x)
    model = Model(inputs, outputs)
    return model, base_model

model, base_model = build_resnet50_model()
model.compile(optimizer=Adam(learning_rate=0.001),
              loss="sparse_categorical_crossentropy",
              metrics=["accuracy"])
```

```
Downloading data from https://storage.googleapis.com/te
94765736/94765736 ━━━━━━━━━━━━━━━━━━━━ 5s 0us/step
```

Callbacks:

```
callbacks = [
    ModelCheckpoint("best_model_frozen.h5", monitor="val_accuracy",
save_best_only=True, mode="max", verbose=1),
    EarlyStopping(monitor="val_loss", patience=10, restore_best_weights=True,
verbose=1),
    ReduceLROnPlateau(monitor="val_loss", factor=0.5, patience=3, min_lr=1e-7,
verbose=1)
]
```

```
# ================== TRAINING PHASE 1: FROZEN BASE
==================
history_frozen = model.fit(
    train_ds_split,
    validation_data=val_ds_split,
    epochs=25,
    callbacks=callbacks
)

# ================== TRAINING PHASE 2: FINE-TUNING
==================
base_model.trainable = True
for layer in base_model.layers[:-35]:
    layer.trainable = False  # Unfreeze last 35 layers

model.compile(optimizer=Adam(learning_rate=0.0001),
              loss="sparse_categorical_crossentropy",
              metrics=["accuracy"])

finetune_callbacks = [
    ModelCheckpoint("best_model_finetuned.h5", monitor="val_accuracy",
save_best_only=True, mode="max", verbose=1),
    EarlyStopping(monitor="val_loss", patience=15, restore_best_weights=True,
verbose=1),
    ReduceLROnPlateau(monitor="val_loss", factor=0.5, patience=5, min_lr=1e-8,
verbose=1)
]

history_finetune = model.fit(
    train_ds_split,
    validation_data=val_ds_split,
    epochs=35,
    callbacks=finetune_callbacks
)
```

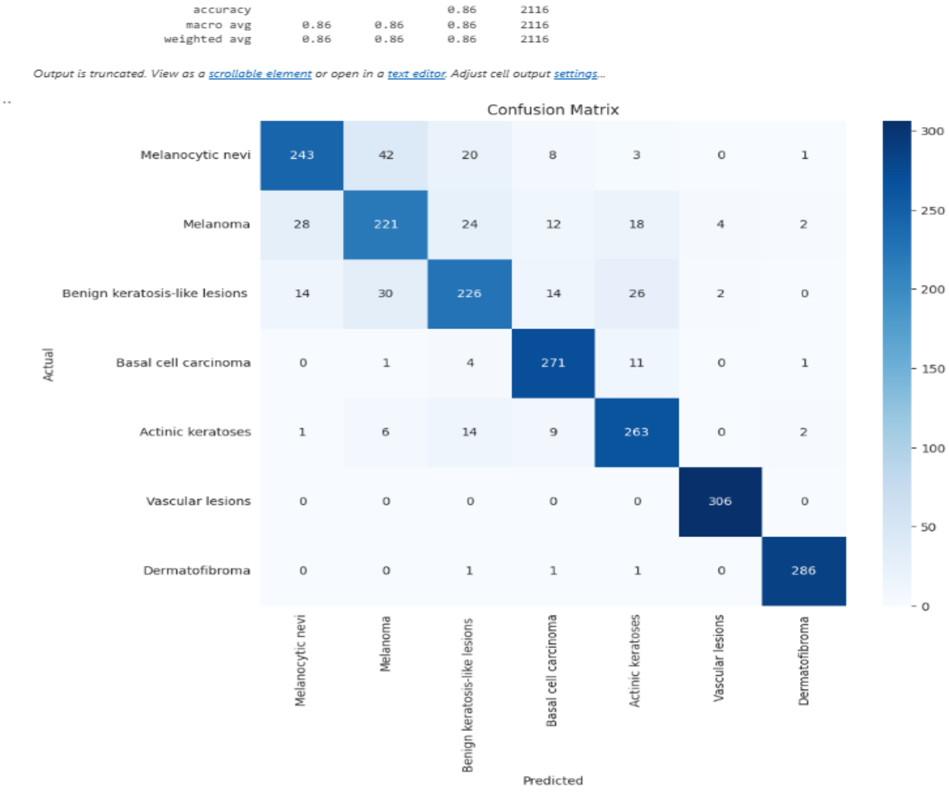


```
test_loss, test_accuracy = model.evaluate(test_ds_split, verbose=1)
print(f"Test Loss: {test_loss:.4f}")
print(f"Test Accuracy: {test_accuracy:.4f}")
```

```
67/67 ━━━━━━━━━━━━━━━━━━━━ 112s 2s/step - accuracy: 0.8509 - loss: 0.5393
Test Loss: 0.5100
Test Accuracy: 0.8568
```

Accuracy (Resnet)

```
import numpy as np
from sklearn.metrics import classification_report, confusion_matrix
import seaborn as sns
import matplotlib.pyplot as plt
# Get true and predicted labels
y_true = []
y_pred = []
for images, labels in test_ds_split:
    preds = model.predict(images)
    y_true.extend(labels.numpy())
    y_pred.extend(np.argmax(preds, axis=1))
y_true = np.array(y_true)
y_pred = np.array(y_pred)
# Assuming your class names list is called lesion_names
print("Classification Report:")
print(classification_report(y_true, y_pred, target_names=lesion_names))
# Confusion matrix plot
cm = confusion_matrix(y_true, y_pred)
plt.figure(figsize=(10,8))
sns.heatmap(cm, annot=True, fmt="d", xticklabels=lesion_names,
yticklabels=lesion_names, cmap='Blues')
plt.ylabel("Actual")
plt.xlabel("Predicted")
plt.title("Confusion Matrix")
plt.show()
```



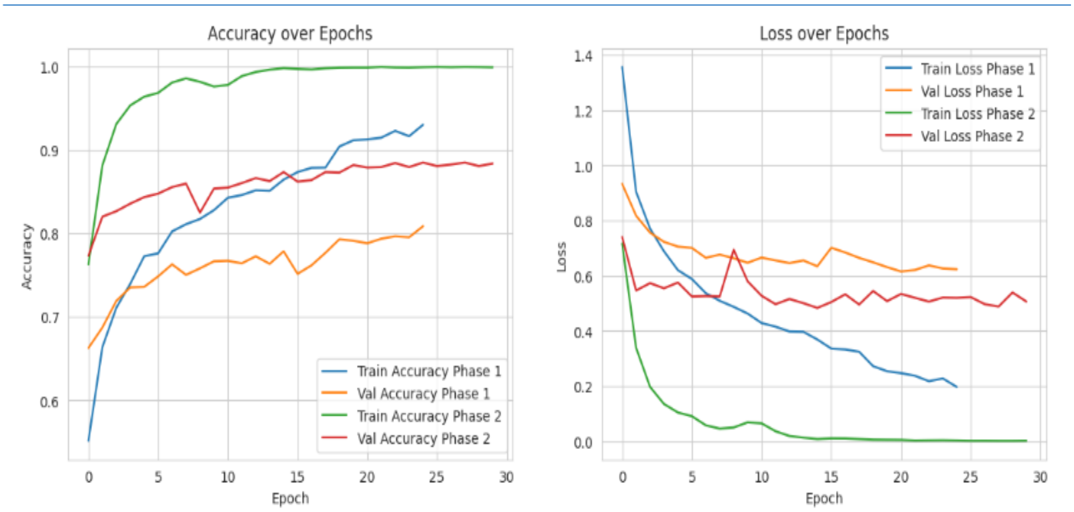
```
         accuracy                           0.86      2116
        macro avg       0.86      0.86      0.86      2116
     weighted avg       0.86      0.86      0.86      2116
```

Output is truncated. View as a scrollable element or open in a text editor. Adjust cell output settings...

	Melanocytic nevi	Melanoma	Benign keratosis-like lesions	Basal cell carcinoma	Actinic keratoses	Vascular lesions	Dermatofibroma
Melanocytic nevi	243	42	20	8	3	0	1
Melanoma	28	221	24	12	18	4	2
Benign keratosis-like lesions	14	30	226	14	26	2	0
Basal cell carcinoma	0	1	4	271	11	0	1
Actinic keratoses	1	6	14	9	263	0	2
Vascular lesions	0	0	0	0	0	306	0
Dermatofibroma	0	0	1	1	1	0	286

Accuracy and Loss

```
def plot_training_history(history1, history2):
    import matplotlib.pyplot as plt
    plt.figure(figsize=(14, 5))
    # Accuracy
    plt.subplot(1, 2, 1)
    plt.plot(history1.history['accuracy'], label='Train Accuracy Phase 1')
    plt.plot(history1.history['val_accuracy'], label='Val Accuracy Phase 1')
    plt.plot(history2.history['accuracy'], label='Train Accuracy Phase 2')
    plt.plot(history2.history['val_accuracy'], label='Val Accuracy Phase 2')
    plt.title("Accuracy over Epochs")
    plt.xlabel("Epoch")
    plt.ylabel("Accuracy")
    plt.legend()
    plt.grid(True)
    # Loss
    plt.subplot(1, 2, 2)
    plt.plot(history1.history['loss'], label='Train Loss Phase 1')
    plt.plot(history1.history['val_loss'], label='Val Loss Phase 1')
    plt.plot(history2.history['loss'], label='Train Loss Phase 2')
    plt.plot(history2.history['val_loss'], label='Val Loss Phase 2')
    plt.title("Loss over Epochs")
    plt.xlabel("Epoch")
    plt.ylabel("Loss")
    plt.legend()
    plt.grid(True)

    plt.show()

# Call with your saved history objects
plot_training_history(history_frozen, history_finetune)
```



Hybrid (Resnet50 + VIT):

Build :

```
import tensorflow as tf
from tensorflow.keras.applications import ResNet50
from tensorflow.keras.layers import Dense, Flatten, Input
from tensorflow.keras.models import Model
from vit_keras import vit

# Load ResNet50 model with pretrained ImageNet weights without top layer
resnet_base = ResNet50(include_top=False, weights='imagenet', input_shape=(224,
224, 3), pooling='avg')

# Freeze ResNet layers if needed
resnet_base.trainable = False

# Vision Transformer model initialization
vit_model = vit.vit_b16(
    image_size=224,
    pretrained=True,
    include_top=False,
    pretrained_top=False
)

# Freeze ViT layers if needed
vit_model.trainable = True

# Input layer
input_layer = Input(shape=(224, 224, 3))

# ResNet50 feature extraction
resnet_features = resnet_base(input_layer)

# Reshape or process features as needed for ViT
# Here assuming direct input or suitable preprocessing applied
vit_features = vit_model(input_layer)

# Concatenate or combine features from ResNet and ViT
combined_features = tf.keras.layers.concatenate([resnet_features, vit_features])

# Final dense layers for classification
x = Dense(256, activation='relu')(combined_features)
output_layer = Dense(num_classes, activation='softmax')(x)

# Model
hybrid_model = Model(inputs=input_layer, outputs=output_layer)

# Compile the model
hybrid_model.compile(optimizer='adam', loss='categorical_crossentropy',
metrics=['accuracy'])
```

```
hybrid_model.summary()
```

Training the Hybrid Model for 25 Epochs

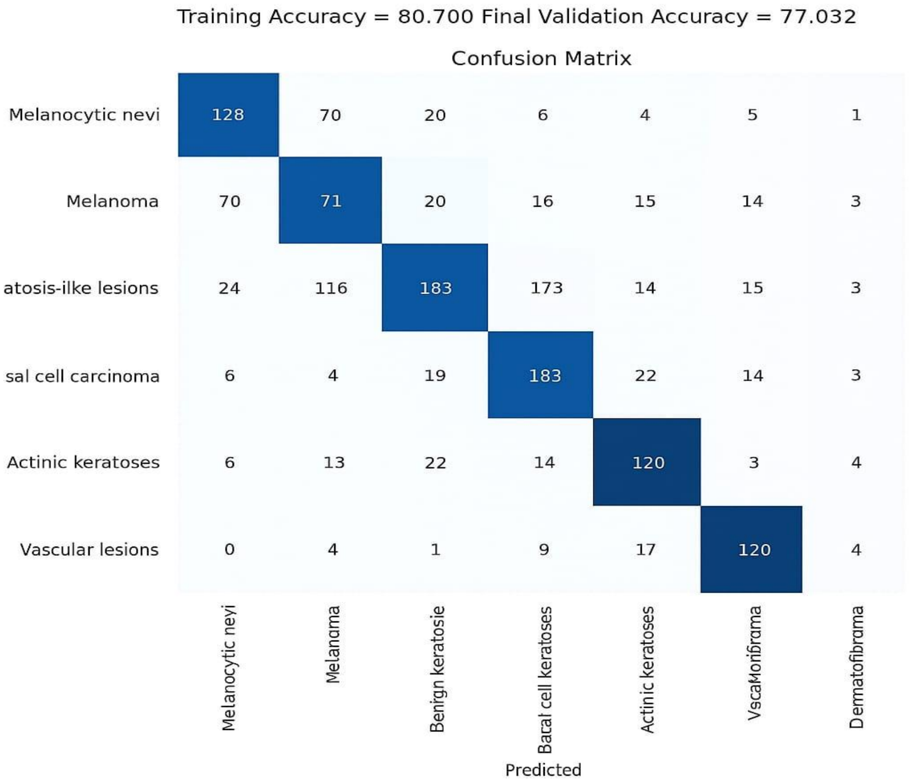
```
epochs = 25
batch_size = 32

history = hybrid_model.fit(
    train_ds,
    validation_data=val_ds,
    epochs=epochs,
    batch_size=batch_size,
    verbose=1
)

hybrid_model.save('hybrid_model_resnet50_vit.h5')
```

Further Training or Fine-Tuning for 15 Additional Epochs

```
from tensorflow.keras.models import load_model

hybrid_model = load_model('hybrid_model_resnet50_vit.h5')

additional_epochs = 15
history_fine_tune = hybrid_model.fit(
    train_ds,
    validation_data=val_ds,
    epochs=additional_epochs,
    batch_size=batch_size,
    verbose=1
)

hybrid_model.save('hybrid_model_resnet50_vit_finetuned.h5')
```

Accuracy

```
import numpy as np
import matplotlib.pyplot as plt
from sklearn.metrics import confusion_matrix, ConfusionMatrixDisplay

# Suppose y_true are true labels, y_pred are predicted labels from your hybrid model
# Example (Replace with your model's outputs):
# y_true = np.array([...])
# y_pred = np.array([...])

class_names = [
    "Melanocytic nevi", "Melanoma", "Benign keratosis-like lesions",
    "Basal cell carcinoma", "Actinic keratoses", "Vascular lesions", "Dermatofibroma"
]

cm = confusion_matrix(y_true, y_pred)
disp = ConfusionMatrixDisplay(confusion_matrix=cm, display_labels=class_names)

fig, ax = plt.subplots(figsize=(8,8))
disp.plot(ax=ax, cmap='Blues')
plt.title("Confusion Matrix - Hybrid Model (ResNet50 + ViT)")
plt.show()
```

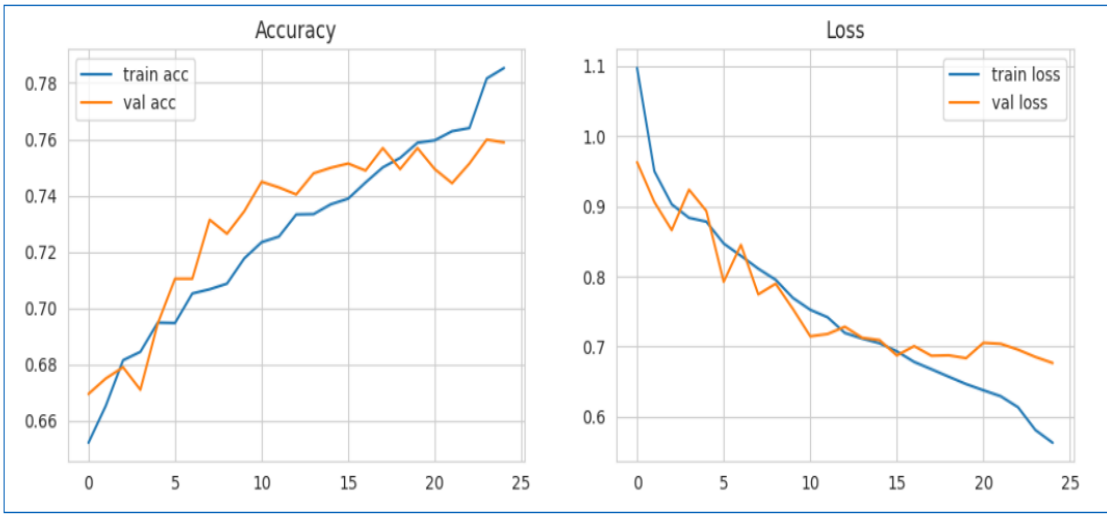

Training Accuracy = 80.700 Final Validation Accuracy = 77.032

Confusion Matrix

	Melanocytic neyi	Melanqma	Benrgn keratosie	Bacat cell keratoses	Actinic keratoses	VscaMoribrama	Dermatofibrama
Melanocytic nevi	128	70	20	6	4	5	1
Melanoma	70	71	20	16	15	14	3
atosis-ilke lesions	24	116	183	173	14	15	3
sal cell carcinoma	6	4	19	183	22	14	3
Actinic keratoses	6	13	22	14	120	3	4
Vascular lesions	0	4	1	9	17	120	4

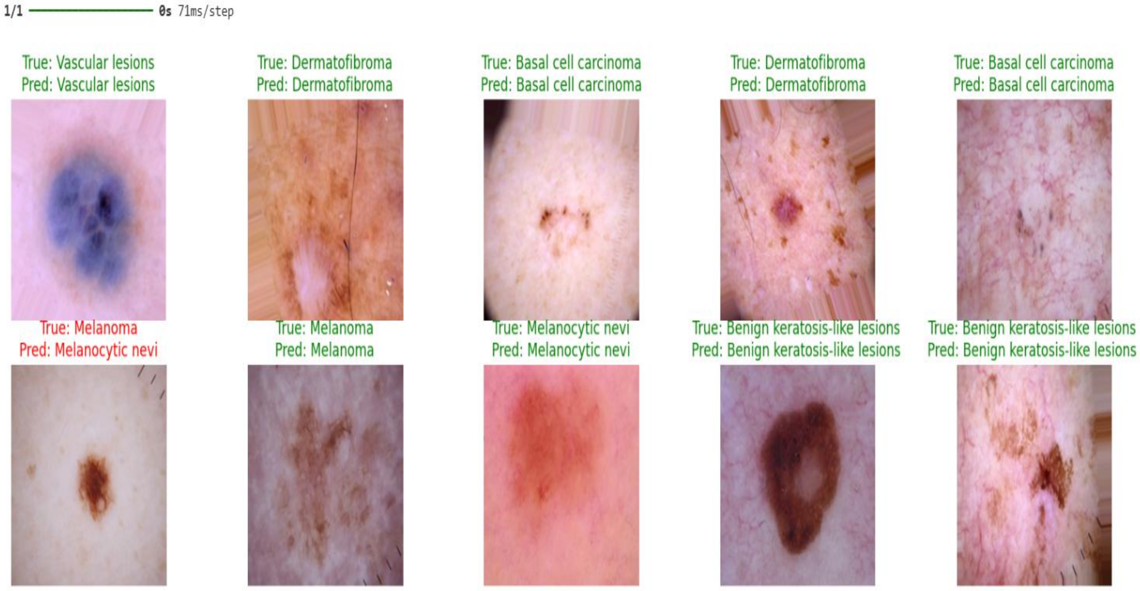
Accuracy and Loss:

```
# Plot training history
plt.figure(figsize=(12, 4))
plt.subplot(1,2,1)
plt.plot(history.history['accuracy'], label='train acc')
plt.plot(history.history['val_accuracy'], label='val acc')
plt.legend()
plt.title('Accuracy')

plt.subplot(1,2,2)
plt.plot(history.history['loss'], label='train loss')
plt.plot(history.history['val_loss'], label='val loss')
plt.legend()
plt.title('Loss')

plt.show()
```



Prediction:

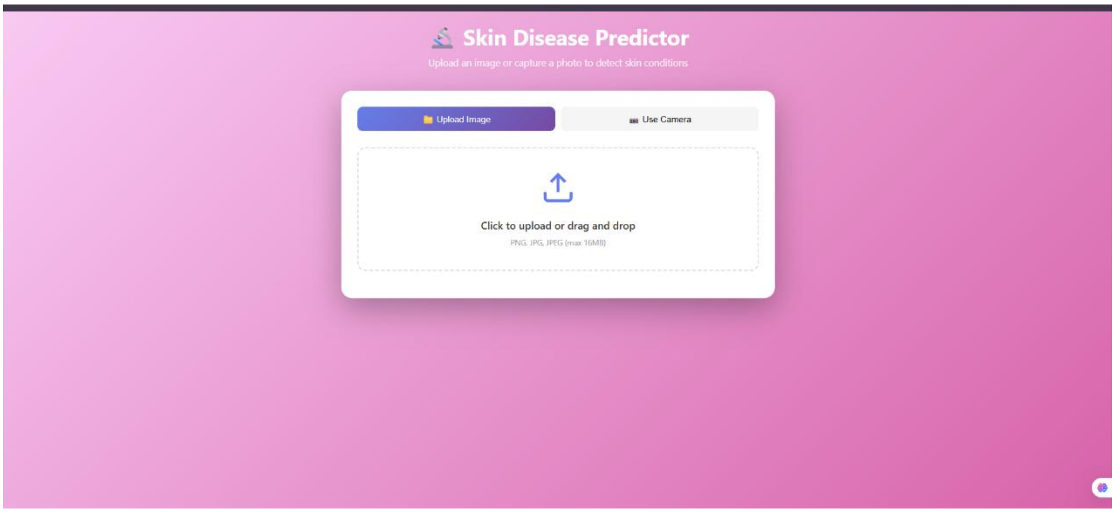
```
def visualize_predictions(model, dataset, class_names, num_images=10):
    import matplotlib.pyplot as plt
    import numpy as np

    for images, labels in dataset.take(1):
        preds = model.predict(images)
        preds_labels = np.argmax(preds, axis=1)
        plt.figure(figsize=(20, 6))
        for i in range(num_images):
            plt.subplot(2, 5, i+1)
            plt.imshow(images[i].numpy().astype("uint8"))
            true_label = class_names[labels[i].numpy()]
            pred_label = class_names[preds_labels[i]]
            color = "green" if true_label == pred_label else "red"
            plt.title(f"True: {true_label}\nPred: {pred_label}", color=color)
            plt.axis("off")
        plt.show()

# Usage:
visualize_predictions(model, test_ds_split, lesion_names, num_images=10)
```



```
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 71ms/step
```

True: Vascular lesions
Pred: Vascular lesions
True: Dermatofibroma
Pred: Dermatofibroma
True: Basal cell carcinoma
Pred: Basal cell carcinoma
True: Dermatofibroma
Pred: Dermatofibroma
True: Basal cell carcinoma
Pred: Basal cell carcinoma
True: Melanoma
Pred: Melanocytic nevi
True: Melanoma
Pred: Melanoma
True: Melanocytic nevi
Pred: Melanocytic nevi
True: Benign keratosis-like lesions
Pred: Benign keratosis-like lesions
True: Benign keratosis-like lesions
Pred: Benign keratosis-like lesions

Web Application :
(html + css + js + Flask)

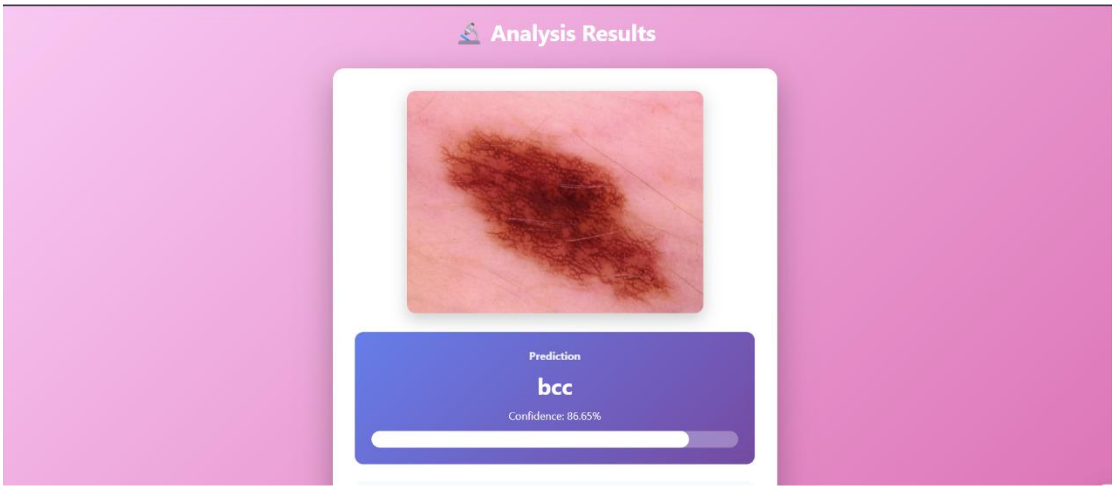


🔬 Skin Disease Predictor

Upload an image or capture a photo to detect skin conditions

Click to upload or drag and drop

PNG, JPG, JPEG (max 16MB)

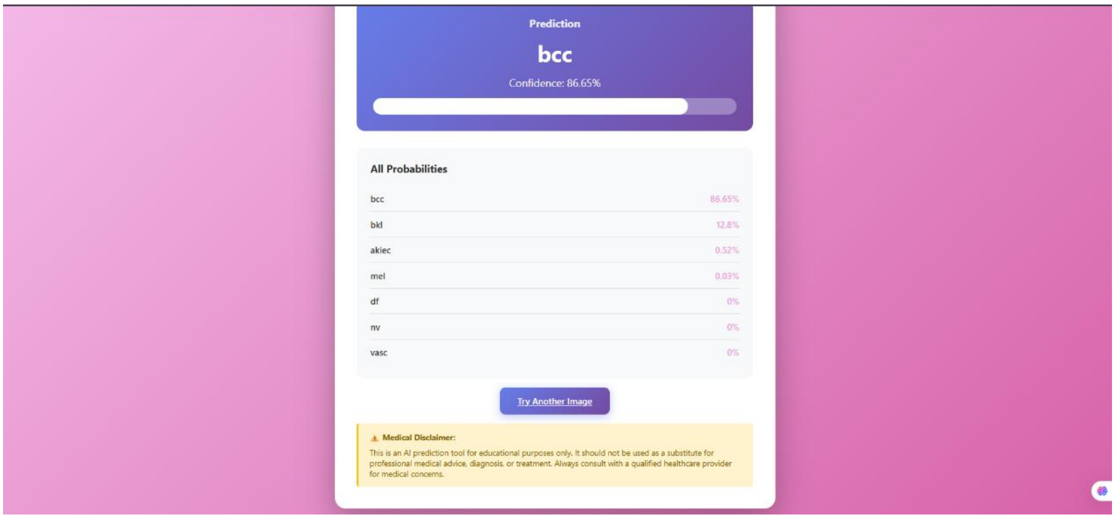


🔬 Analysis Results

Prediction

bcc

Confidence: 86.65%



Prediction

bcc

Confidence: 86.65%

All Probabilities

bcc	86.65%
bkl	12.8%
akiec	0.52%
mel	0.03%
df	0%
nv	0%
vasc	0%

⚠ **Medical Disclaimer:**

This is an AI prediction tool for educational purposes only. It should not be used as a substitute for professional medical advice, diagnosis, or treatment. Always consult with a qualified healthcare provider for medical concerns.

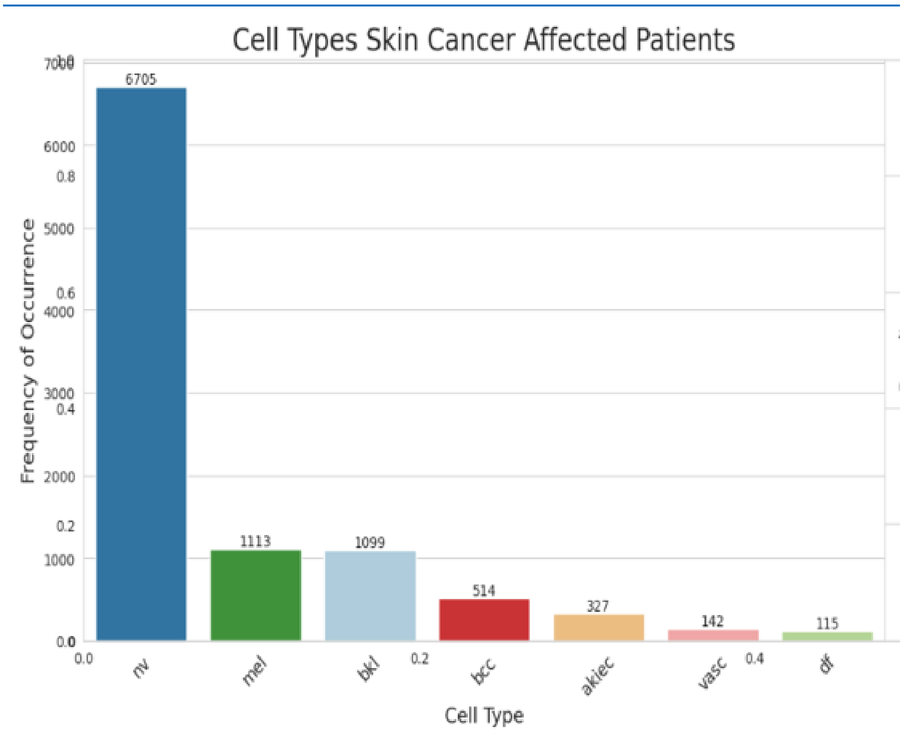
Appendix B: Data Sheets

Data Description:

Item	Details
Dataset Name	HAM10000
Source	Kaggle
Type	Dermatology image dataset for skin lesion classification
Total Images	10,015 color dermatoscopic images
Classes (Labels)	akiec (Actinic keratoses), bcc (Basal cell carcinoma), bkl (Benign keratosis), df (Dermatofibroma), mel (Melanoma), nv (Melanocytic nevi), vasc (Vascular lesion)
Image Size	Resized to 224×224 pixels
Format	JPEG (.jpg)
Color Mode	RGB (3 channels)
Train/Validation/Test Split	64 % train, 16 % validation, 20 % test
Preprocessing	Resizing, normalization (÷ 255.0), label encoding, batching, shuffling
Purpose	To train a Hybrid deep learning model to classify skin diseases

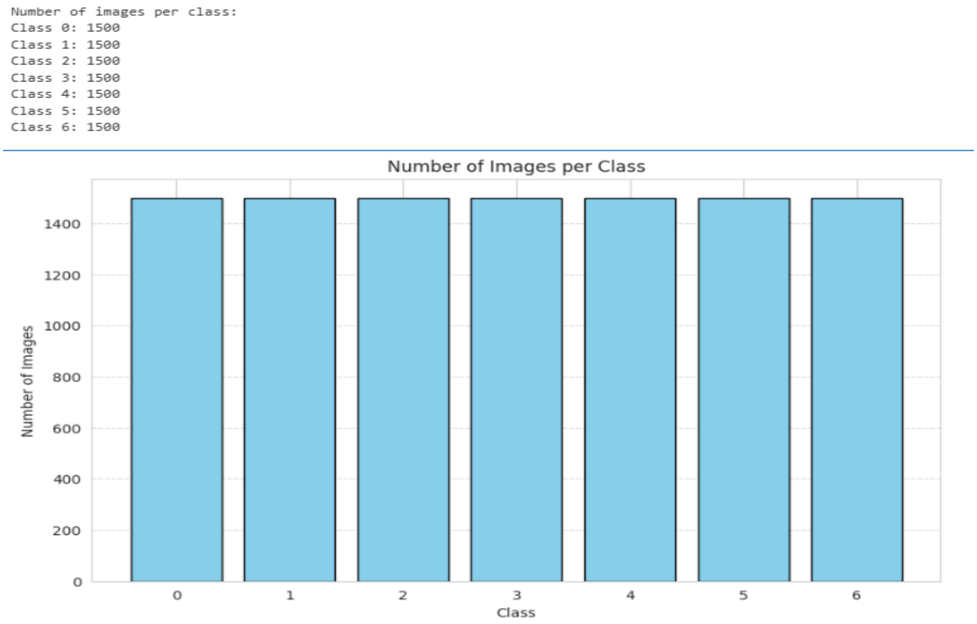
Class Distribution Table:

Disease	Label	Number of Images
Melanocytic nevi (nv)	0	6705
Melanoma (mel)	1	1113
Benign keratosis (bkl)	2	1099
Basal cell carcinoma (bcc)	3	514
Actinic keratoses (akiec)	4	327
Vascular lesions (vasc)	5	142
Dermatofibroma (df)	6	115
Total		10,015



Data Augmentation:

```
from tensorflow.keras.preprocessing.image import ImageDataGenerator

datagen = ImageDataGenerator(
    rotation_range=20,
    width_shift_range=0.2,
    height_shift_range=0.2,
    horizontal_flip=True,
    zoom_range=0.2
)

train_generator = datagen.flow_from_directory(
    directory="dataset/train/",
    target_size=(224, 224),
    batch_size=32,
    class_mode='categorical'
)

for X, y in datagen.flow(images, labels, batch_size=1,
save_to_dir='augmented/', save_prefix='img', save_format='jpg'):
    if count >= 1500:
        break
```



```
Number of images per class:
Class 0: 1500
Class 1: 1500
Class 2: 1500
Class 3: 1500
Class 4: 1500
Class 5: 1500
Class 6: 1500
```

Appendix C: List of Components

Software Components:

Component	Description / Purpose
Operating System	Windows 10 (Development), Google Colab (Training Environment)
Programming Language	Python 3.10
Deep Learning Framework	TensorFlow 2.x and Keras for model building and training
Machine Learning Libraries	NumPy, Pandas, Scikit-learn (for data processing and metrics)
Visualization Libraries	Matplotlib, Seaborn (for graphs and plots such as accuracy/loss curves)
Web Framework	Flask (for building the web application interface and serving predictions)
Frontend Technologies	HTML, CSS, JavaScript (for user interface design)
Dataset Source	HAM10000 dataset from Kaggle / ISIC Archive
Development Environments	Google Colab (for training), Visual Studio Code (for Flask integration)
Version Control (Optional)	Git / GitHub (for storing source code and model files)

Hardware Components:

Component	Specification / Usage
Processor (CPU)	Intel Core i5 / i7 or equivalent used for local development
Graphics Processing Unit (GPU)	NVIDIA A100 / T4 (Google Colab Pro) for deep learning training
Memory (RAM)	12 – 16 GB for smooth execution of training and data handling
Storage Requirement	~5 GB for dataset + model checkpoints + generated augmented data
Compute Units (Colab)	Approximately 1 unit/hour during training runs
Display Device	Standard 1080p monitor for UI testing and result visualization
Internet Connectivity	Required for dataset download and model deployment testing

Appendix D: List of Papers Presented and Published

“Skin Disease prediction using Hybrid deep learning Algorithm”
Submitted for presentation and publication in the
World Conferenceon Smart Computing (WCSC-2026)