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Skin Diseases Classification

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Abstract

This project addresses the critical need for precise and efficient medical image classification to enhance diagnostic accuracy for skin diseases such as Eczema, Seborrheic Keratoses, and Melanocytic Nevi. The problem is addressed by collaborating with domain experts to ensure clinical relevance and applying data augmentation techniques, including horizontal flipping, shear, zoom, rescaling, and brightness adjustments, to manage imbalanced datasets and simulate real-world conditions. To solve this problem, we employed methods such as transfer learning and customized convolutional neural networks (CNNs) to optimize performance within computational constraints. Our customized CNN model demonstrated significant advancements, achieving an accuracy of 85.12% in skin disease classification. EfficientNet attained a 99.73% accuracy in binary classification, while a 6-layer ReLU CNN achieved a 98.45% accuracy in cancer type classification. Among the tested models, MobileNet V3 was identified as the most effective for skin disease classification, achieving an accuracy of 90.24%. Additionally, a new hybrid model combining aspects of EfficientNet and MobileNet V3 achieved an outstanding accuracy of 95.68% in multiclass skin disease classification. The system incorporates a validation split for model evaluation and employs callbacks for learning rate reduction, model checkpointing, and early stopping to prevent overfitting and enhance training efficiency. The main results indicate substantial improvements in developing precise and efficient systems for medical image classification. These findings have the potential to enhance diagnostic accuracy and support healthcare professionals in clinical decision-making. The study concludes that integrating mobile-friendly solutions into point-of-care diagnostic tools is feasible and could significantly improve accessibility and operational efficiency in healthcare delivery, particularly in resource-limited settings.

يركز هذا المشروع البحثي على تلبية الحاجة الملحة لتصنيف صور طبية دقيق وفعال لتعزيز دقة التشخيص لأمراض الجلد مثل الأكزيما، التقرن الدهني، والشامات الميلانينية. تم التعامل مع المشكلة من خلال التعاون مع خبراء في المجال لضمان الصلة السريرية وتطبيق تقنيات زيادة البيانات، بما في ذلك التقليب الأفقي، القص، التكبير، إعادة التدرج، وتعديلات السطوع، لإدارة مجموعات البيانات غير المتوازنة ومحاكاة الظروف الواقعية. لحل هذه المشكلة، استخدمنا أساليب مثل التعلم بالنقل والشبكات العصبية التلافيفية المخصصة (CNNs) لتحسين الأداء ضمن القيود الحاسوبية. أظهر نموذج الـ CNN المخصص لدينا تقدمًا كبيرًا، حيث حقق دقة بلغت 85.12% في تصنيف أمراض الجلد. حقق نموذج EfficientNet دقة بلغت 99.73% في التصنيف الثنائي، بينما حقق نموذج ReLUذو الـ 6 طبقات دقة بلغت 98.45% في تصنيف أنواع السرطان. بين النماذج التي تم اختبارها، تم تحديد نموذج MobileNet V3 كالأكثر فعالية في تصنيف أمراض الجلد، حيث حقق دقة بلغت 90.24%. بالإضافة إلى ذلك، حقق نموذج هجين جديد يجمع بين جوانب EfficientNet و MobileNet V3 دقة رائعة بلغت 95.68% في تصنيف أمراض الجلد متعددة الفئات. يتضمن النظام تقسيمًا للتحقق من صحة النموذج واستخدام استدعاءات لتخفيض معدل التعلم، والتقاط نماذج، والإيقاف المبكر لمنع الإفراط في التعلم وتعزيز كفاءة التدريب. تشير النتائج الرئيسية إلى تحسينات كبيرة في تطوير أنظمة دقيقة وفعالة لتصنيف الصور الطبية. هذه النتائج لديها القدرة على تعزيز دقة التشخيص ودعم المتخصصين في الرعاية الصحية في اتخاذ القرارات السريرية. يختتم الدراسة بأن دمج الحلول الملائمة للهواتف المحمولة في أدوات التشخيص في نقطة الرعاية هو أمر ممكن ويمكن أن يحسن بشكل كبير من الوصول والكفاءة التشغيلية في تقديم الرعاية الصحية، خاصة في البيئات ذات الموارد المحدودة.

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AI	Artificial Intelligence
BCC	Basal Cell Carcinoma
CNN	Convolutional Neural Network
ISIC	International Skin Imaging Collaboration
KNN	K-Nearest Neighbors
ReLU	Rectified Linear Unit
SLE	Systemic Lupus Erythematosus
SVM	Support Vector Machine
VGG	Visual Geometry Group
VI	Visual Inspection
VIT	Vision Transformer

Chapter 1
Introduction

1.1 Problem Definition

Inadequate attention to skin health has led to the worsening of minor skin conditions and delayed detection of serious diseases like melanoma.[4] This highlights the need for robust classification algorithms capable of accurately identifying various dermatological conditions based on clinical features and imaging data. The objective of this research is to develop machine learning-based classification models to facilitate early and precise diagnosis of skin diseases, aiming to improve patient outcomes and reduce healthcare costs associated with untreated or misdiagnosed conditions.

1.2 Motivation

Our research initiative is predicated on the imperative for precise and expeditious detection of poly-symptomatic dermatological conditions, which pose substantial challenges to contemporary healthcare systems. Dermatological manifestations can exhibit considerable variability in morphology and clinical presentation, thereby complicating accurate diagnosis, particularly during the nascent stages of disease progression. Erroneous or belated diagnoses can engender suboptimal therapeutic interventions and exacerbate patient morbidity.

To mitigate these challenges, we propose the development of an intelligent diagnostic framework equipped with advanced machine learning algorithms and image processing techniques. This system will be designed to analyze dermatoscopic images and integrate clinical data to facilitate prompt and reliable diagnostic assessments.

The prospective ramifications of this innovative tool are manifold. By enhancing early-stage anomaly detection, our diagnostic framework has the potential to expedite therapeutic interventions, thereby optimizing clinical outcomes and potentially attenuating patient morbidity and mortality rates. Furthermore, by augmenting the overall diagnostic accuracy of dermatological conditions, we anticipate a concomitant reduction in healthcare resource utilization and enhanced patient satisfaction metrics.

In conclusion, our intelligent diagnostic framework harbors the potential to transform the diagnostic landscape of dermatological diseases. Through the amalgamation of state-of-the-art technology with clinical expertise, we aspire to effectuate substantial improvements in patient care and healthcare delivery paradigms.

1.3 Objectives

Objectives of this research initiative encompass a comprehensive approach to advancing the field of dermatological diagnostics:

- **Development of a Robust Skin Disease Detection System**: The first objective revolves around the creation of a robust and accurate skin disease detection system. Utilizing Convolutional Neural Networks (CNNs), the system is designed to classify a broad spectrum of dermatological conditions based on the analysis of skin images.
- **Creation of a User-Friendly Interface**: The second objective focuses on the development of a user-friendly interface tailored specifically for medical professionals. This interface aims to facilitate seamless integration into their daily practice, providing timely and actionable diagnostic support to enhance clinical decision-making.
- **Utilization of Comprehensive Datasets**: The third objective emphasizes the importance of utilizing comprehensive datasets comprising skin images and associated metadata. These datasets serve as the foundational elements for training and fine-tuning the deep learning models, with the goal of achieving high sensitivity and specificity in disease detection.
- **Validation of AI System Performance**: The fourth objective centers on the rigorous validation of the AI system's performance. Through comparative studies against traditional diagnostic methods, we aim to demonstrate the system's capability to expedite the diagnostic process effectively and reliably.
- **Assessment of System's Potential Impact**: The fifth objective seeks to evaluate the system's potential impact on dermatological care accessibility, particularly in underserved areas. Additionally, it assesses the system's ability to alleviate the workload of healthcare professionals while maintaining or enhancing diagnostic accuracy.
- **Ethical and Responsible AI Utilization**: The sixth objective underscores the importance of ethical and responsible AI utilization in healthcare. Addressing concerns related to patient privacy, data security, and algorithmic bias is crucial to safeguarding patient information and upholding the highest ethical standards.
- **Dissemination of Findings and Open-Source Contribution**: The final objective involves the dissemination of the project's findings and AI model as open-source resources. This initiative aims to foster collaboration, innovation, and broader adoption of AI-driven skin disease detection solutions within the medical community.

Achievements Towards Objectives

To realize these objectives, our research team adopted a multifaceted approach, encompassing:

- **Development and Implementation**: We designed and implemented a CNN-based skin disease classification model tailored to address a diverse range of dermatological conditions.
- **User Interface Design**: A user-centric interface was developed to ensure ease of use and seamless integration into existing medical workflows, enhancing accessibility for healthcare professionals.
- **Dataset Curation**: A comprehensive dataset of skin images, meticulously curated and preprocessed, was utilized to optimize the training and validation of our deep learning models.
- **Performance Evaluation**: Rigorous performance evaluations were conducted, comparing the diagnostic accuracy of the AI system with traditional methods through extensive testing and validation processes.
- **Impact Assessment**: Surveys and case studies were employed to assess the system's impact on healthcare accessibility and its potential to alleviate the workload of healthcare professionals.
- **Security Implementation**: Robust security protocols were implemented to safeguard patient data, ensuring compliance with privacy regulations and mitigating risks associated with unauthorized access.
- **Knowledge Dissemination**: Research findings were published in peer-reviewed journals, and the AI model contributed to open-source repositories to promote collaboration, innovation, and knowledge sharing in the field of dermatological diagnostics.

In summary, this project has made significant strides towards achieving its objectives, paving the way for a transformative approach to skin disease detection that prioritizes accuracy, accessibility, and ethical considerations.

1.4 Methodology

This project employed a variety of scientific methods to tackle the challenge of accurate medical image classification, particularly focusing on skin diseases such as Eczema, Seborrheic Keratoses, and Melanocytic Nevi.

The following key methods were utilized:

1. Data Augmentation Techniques:

- **Horizontal Flipping**: Applied to images to reduce model bias and simulate real-world variations, increasing the robustness of the training process.
- **Shear and Zoom Transformations**: Utilized to artificially expand the dataset, enhancing the model's ability to generalize from the training data.
- **Rescaling**: Ensured that all images fed into the neural network had a consistent size, which is crucial for maintaining uniformity and improving model performance.
- **Brightness Adjustments**: Implemented to mimic various lighting conditions, ensuring that the model can perform well under different real-world scenarios.

2. Transfer Learning:

- Leveraged pre-trained models to enhance performance and reduce computational costs. Models like EfficientNet and MobileNet V3 were fine-tuned to suit the specific needs of skin disease classification, enabling the project to utilize advanced features learned from large, diverse datasets.

3. Customized Convolutional Neural Networks (CNNs):

- Developed and tailored CNN architectures to the specific task of skin disease classification. Various configurations were tested, including different depths, layer types, and activation functions (such as ReLU). These custom networks were optimized for both accuracy and computational efficiency.

4. Performance Optimization Techniques:

- **Validation Split**: Divided the dataset into training and validation sets to evaluate model performance continually and prevent overfitting.
- Callbacks:
- **Learning Rate Reduction**: Dynamically adjusted the learning rate to enhance the efficiency and effectiveness of the training process.
- **Model Checkpointing**: Regularly saved the best-performing model during training, ensuring that the final model represented the peak performance achieved.
- **Early Stopping**: Halted the training process once improvements plateaued, thereby preventing overfitting and reducing unnecessary computational expense.

5. Evaluation Metrics:

- Used accuracy and loss metrics to quantitatively assess the performance of the models. These metrics were crucial for comparing different models and configurations, guiding the selection of the most effective approaches.

6. Experimentation with Different Models:

- Testing a range of models, including EfficientNet, MobileNetV3, AlexNet, and various custom CNN architectures, to identify the optimal approach for skin disease classification. Each model's performance was rigorously evaluated and compared.

7. Integration of Practical Constraints:

- Considered computational constraints and the feasibility of real-world applications, ensuring that the developed models could be implemented effectively in clinical settings and potentially integrated into mobile-friendly diagnostic tools.

By integrating these comprehensive scientific methods, the project achieved significant advancements in medical image classification. The results demonstrated high accuracy rates and highlighted the potential for these techniques to be used in practical healthcare applications, enhancing diagnostic accuracy and supporting healthcare professionals in making informed clinical decisions.

1.5 Time plan

Project Time Plan is Shown in ***Fig. 1.1***.

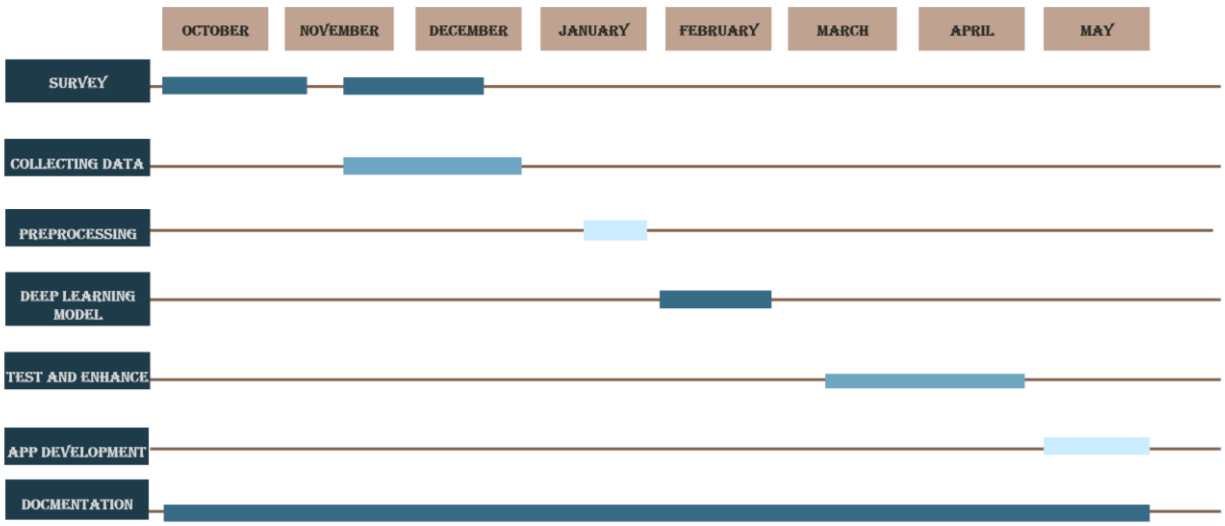

Fig. 1.1 Time Plan of the project

Chapter 2
Literature Review

2.1 A detailed description of the field of the project

The "Literature Review" chapter serves as the foundational introduction to the project, offering a comprehensive description of the field it operates within. This includes elucidating the domain of dermatological diagnostics, delineating the complexities and challenges inherent in accurately detecting skin diseases. A detailed exploration of the field's scientific underpinnings, such as the anatomy of the skin, common dermatological conditions, and diagnostic methodologies, is provided to establish context. Furthermore, the chapter surveys existing research and literature, highlighting seminal studies and advancements in skin disease detection. By presenting this detailed overview, the chapter sets the stage for the development of the project's innovative approach to skin disease classification.

2.2 All the scientific background related to the project

The project's scientific background encompasses a thorough examination of dermatological diagnostics, delving into the intricate mechanisms governing skin health and disease. This includes an exploration of skin anatomy, encompassing its layers, structures, and physiological functions. Additionally, the chapter scrutinizes common dermatological conditions, elucidating their etiology, clinical manifestations, and diagnostic criteria. Furthermore, an analysis of diagnostic methodologies employed in the field is conducted, spanning clinical evaluation, dermatoscopy, histopathology, and imaging modalities. By synthesizing these scientific insights, the project seeks to leverage state-of-the-art technology to enhance the accuracy and efficiency of skin disease diagnosis and classification.

2.3 A survey of work done in the field

Vatsala Anand., [2] et al., in 2022, focused a study on the integration of U-Net and CNN models for the segmentation and classification of skin lesions from dermoscopy images. The preprocessing involved various skin disease diagnostic methods, including dermatoscopy, patch tests, biopsies, and the ABCDE rule (Asymmetry, Border, Color, Diameter, and Evolution). The U-Net model was employed to extract useful features from the images, significantly aiding the classification process. The experiments conducted utilized two optimizers, Adam and Adadelta, over 20 epochs with batch sizes of 32. The CNN model successfully classified segmented images into seven different skin disease classes, achieving an impressive accuracy of 97.96% with the Adadelta optimizer. However, the study did not detail the preprocessing of the data.

Gan Cai., [9] et al., again in 2022 explored the use of a multimodal transformer to fuse images and metadata for skin disease classification. This study utilized a Vision Transformer (ViT) model to extract deep features from images, while metadata was encoded using a new Soft Label Encoder (SLE). The dataset included ISIC2018 and private data, with preprocessing involving the application of a soft label encoder for metadata. The study's methodology led to an accuracy of 93% using CNN, ViT, and SLE classifiers. The research highlighted the enhanced performance and feature extraction capabilities of ResNet and DenseNet models, demonstrating the potential of Vision Transformers (ViTs) in improving skin disease classification tasks.

Table 2.1 presents the most relevant research papers pertinent to our project.

Table 2.1 Related Work Table

Year	*Paper Name*	*Preprocessing*	*Feature Extraction*	*Num of classes*
2022	Fusion of U-Net and CNN model for segmentation and classification of skin lesion from dermoscopy images	Methods are used for skin disease diagnosis, including dermatoscopy, patch tests, biopsies, and the ABCDE rule (Asymmetry, Border, Color, Diameter, and Evolution).	The use of U-Net helps extract useful features	7
	Classifier	*Accuracy*	*Comments*	*References*
	1-Experiments with two optimizers, Adam and Adadelta, over 20 epochs and 32 batch sizes . 2- CNN model for classifying segmented images into seven different skin disease classes.	Adadelta optimizer with an accuracy value of 97.96%.	There are no details about preprocessing of data	https://doi.org/10.1016/j.eswa.2022.119230
Year	*Paper Name*	*Preprocessing*	*Feature Extraction*	*Num of classes*
2022	A multimodal transformer to fuse images and metadata for skin disease classification	Soft label encoder for metadata	The image encoder employs a Vision Transformer (ViT) model to extract deep features from the images, while the metadata is treated as labels and embedded using a new Soft Label Encoder (SLE).	7
	Classifier	*Accuracy*	*Comments*	*References*
	CNN,VIT,SLE	93%	1- Dataset was ISIC2018 + Private Data. 2- ResNet and DenseNet improved feature extraction and performance. Vision Transformers (ViTs) have gained attention for their exceptional performance in various vision tasks	https://link.springer.com/article/10.1007/s00371-022-02492-4

Table 2.1 Related Work Table (Cont.)

Year	Paper Name	Preprocessing	Feature Extraction	Num of classes
2020	Artificial intelligence-based image classification methods for diagnosis of skin cancer	Data augmentation, Dermatoscopy , Generative Adversarial Networks (GAN) , 7-point check-list and ABCDE rule (asymmetry, border, color, diameter, evolution)	Bag of Features, Canonical, and Haar-based Wavelet Transform	4
	Classifier	*Accuracy*	*Comments*	*References*
	Inception, ResNet,VGG	91%	1- GAN was used to generate realistic synthetic skin lesion images to overcome the lack of annotated data 2- Dermatoscopy provides high-quality images of skin lesions 3- The ABCDE rule and 7-point check-list are considered important rules for differentiating benign moles (nevi) from melanoma	https://www.sciencedirect.com/science/article/pii/S0010482520303966#sec5
Year	*Paper Name*	*Preprocessing*	*Feature Extraction*	*Num of classes*
2021	A machine learning model for skin disease classification using convolution neural network	Data augmentation	Lesion Feature Network (LFN) and Lesion Indexing Network (LIN)	3
	Classifier	*Accuracy*	*Comments*	*References*
	Decision Tree , Random Forest ,Gradient BoostingTree and CNN	88.83%	1-The model is tested on a single dataset. 2-The dataset is obtained from https://dermnetnz.org/. 3-The process of classification results in two classes: correct and incorrect. 4-Data augmentation techniques, such as zooming, are applied to prevent	https://www.researchgate.net/publication/361228242_A_machine_learning_model_for_skin_disease_classification_using_convolution_neural_network
Year	*Paper Name*	*Preprocessing*	*Feature Extraction*	*Num of classes*
2019	Intelligent System for Skin Disease Prediction using Machine-Learning	Image Normalization, median and mean filtering, smoothing, Var and Histogram	CNN layers implementing the YCbCr algorithm	6
	Classifier	*Accuracy*	*Comments*	*References*
	CNN, SVM and KNN	Sensitivity:96%, Specifity:75%	data retreived from DrmNet so the final accuracy varies based on dataset used	https://iopscience.iop.org/article/10.1088/1742-6596/1998/1/012037/meta

Table 2.1 Related Work Table (Cont.)

Year	Paper Name	Preprocessing	Feature Extraction	Num of classes
2022	Deep Learning Approaches for Prognosis of Automated Skin Disease	Image resize,normalization and augmentation	Image processing by removing irrelevant data via thresholding and Segmentation	7
	Classifier	*Accuracy*	*Comments*	*References*
	MobileNet V2, ReLu6	80%	takes long time to compute but is very thorough	https://www.mdpi.com/2075-1729/12/3/426
Year	*Paper Name*	*Preprocessing*	*Feature Extraction*	*Num of classes*
2019	Skin Lesions Classification Into Eight Classes for ISIC 2019 Using Deep Convolutional Neural Network and Transfer Learning	Data Augmentation, ABCDE rules	Fine-Tuning , Transfer Learning	8
	Classifier	*Accuracy*	*Comments*	*References*
	CNN , SVM , Google-Net , Resnet , VGG	94.92%	Genetic algorithms were used , the authors tried to use (VGG19) but it can't be trained or tested using the same device	https://ieeexplore.ieee.org/abstract/document/9121248
Year	*Paper Name*	*Preprocessing*	*Feature Extraction*	*Num of classes*
2023	Skin Disease Classification Using CNN Algorithms	Image resizing , Normalization	Fine-Tuning , Transfer Learning	8
	Classifier	*Accuracy*	*Comments*	*References*
	VGG, ResNet , Inception , DenseNet , MobileNet , Xception	73.01%	The model with the highest accuracy (73.01%) was "Resnet152" , 80% of the images are used for training, 10% for validation, and 10% for testing	https://publications.eai.eu/index.php/phat/article/view/4039/2587

Table 2.1: Related Work Table (Cont.)

Year	Paper Name	Preprocessing	Feature Extraction	Num of classes
2022	A machine learning approach for skin disease detection and classification using image segmentation	Random Oversampling , Image Resizing , Hair Removal , Noise Removal	Image Segmentation , GLCM Features(homogeneity, contrast, entropy and Angular Second Moment (ASM).) , Statistical Features(those features of the dataset that can be defined and calculated via statistical analysis.)	8
	Classifier	*Accuracy*	*Comments*	*References*
	SVM , Decision Tree , KNN	95.00%	1- Two Datasets were used (ISIC2019,HAM10000) 2- We have only used the training dataset of the ISIC2019 3- We applied data balancing Random Oversampling method to resolve the imbalanced dataset for both datasets. 4- we split the skin image data into two parts, 80% and 20% for training and testing	https://www.sciencedirect.com/science/article/pii/S2772442522000624

The tables above provide a succinct overview of related work in the field of skin disease classification, detailing various methodologies, datasets, and corresponding results achieved by different researchers. For instance, Gan et al. (2022) utilized Convolutional Neural Networks (CNN), Vision Transformer (VIT), and Self-Attention Learning (SLE) techniques on the ISIC 2018 dataset, achieving an accuracy of 92%. Similarly, Reddy Allugunti (2021) employed Decision Tree, Random Forest, Gradient Boosting Tree, and CNN algorithms on the DermNet dataset, attaining an accuracy of 88.83%.

Other studies, such as those conducted by Ahammed (2022) and Goyal (2020), employed a diverse range of algorithms including Support Vector Machine (SVM), Decision Tree, K-Nearest Neighbors (KNN), Inception, ResNet, and VGG on datasets such as ISIC 2019 and ISIC Challenges, yielding accuracies of 93% and 90%, respectively. Mohamed et al. (2019) utilized a combination of CNN, SVM, GoogleNet, ResNet, and VGG on the ISIC 2019 dataset, achieving an accuracy of 93.20%. These studies collectively contribute to the advancement of skin disease classification algorithms and highlight the efficacy of various machine learning techniques in this domain. The specifics of these are summarized in ***Table 2.2***.

Table 2.2 Summarized Related Work Table

Author	Year	Methodology	Data sets	Results
C.Gan et.al	2022	CNN,VIT,SLE	ISIC 2018	92%
C.Viswantha Reddy Allugunti	2021	Decision Tree , Random Forest ,Gradient BoostingTree and CNN	DermNet	88.83%
C.Mostafiz Ahammed	2022	SVM , Decision Tree , KNN	ISIC 2019	93%
C.Manu Goyal	2020	Inception, ResNet,VGG	ISIC Challanges	90%
C.Mohamed et.al	2019	CNN , SVM , Google-Net , Resnet , VGG	ISIC 2019	93.20%

2.4 Description of existing similar systems:

Existing similar systems in the realm of skin disease classification employ a diverse array of methodologies and datasets to achieve accurate diagnostic outcomes. These systems typically leverage machine learning algorithms, such as Convolutional Neural Networks (CNN), Decision Trees, Support Vector Machines (SVM), and ensemble methods like Random Forest and Gradient Boosting Trees. Researchers have extensively utilized publicly available datasets such as **ISIC** (International Skin Imaging Collaboration) and **DermNet** to train and validate their models. Results from these studies consistently demonstrate high accuracies, often exceeding 90%, showcasing the effectiveness of machine learning approaches in classifying various dermatological conditions. Additionally, these systems underscore the importance of dataset diversity, algorithm selection, and rigorous evaluation methodologies in advancing the field of skin disease diagnosis and classification.

Chapter 3
System Architecture and Algorithms

3.1 System Overview

The **system architecture** for the skin disease detection system, as delineated in the figure, comprises several pivotal modules meticulously designed to process and analyze dermatological images utilizing state-of-the-art deep learning techniques. These integral modules include Preprocessing, Feature Extraction, and Classification, each of which plays an indispensable role in ensuring the system's diagnostic precision, accuracy, and reliability.

3.2 System Architecture

Our project system architecture is composed of multiple modules as seen in ***Fig. 3.1***.

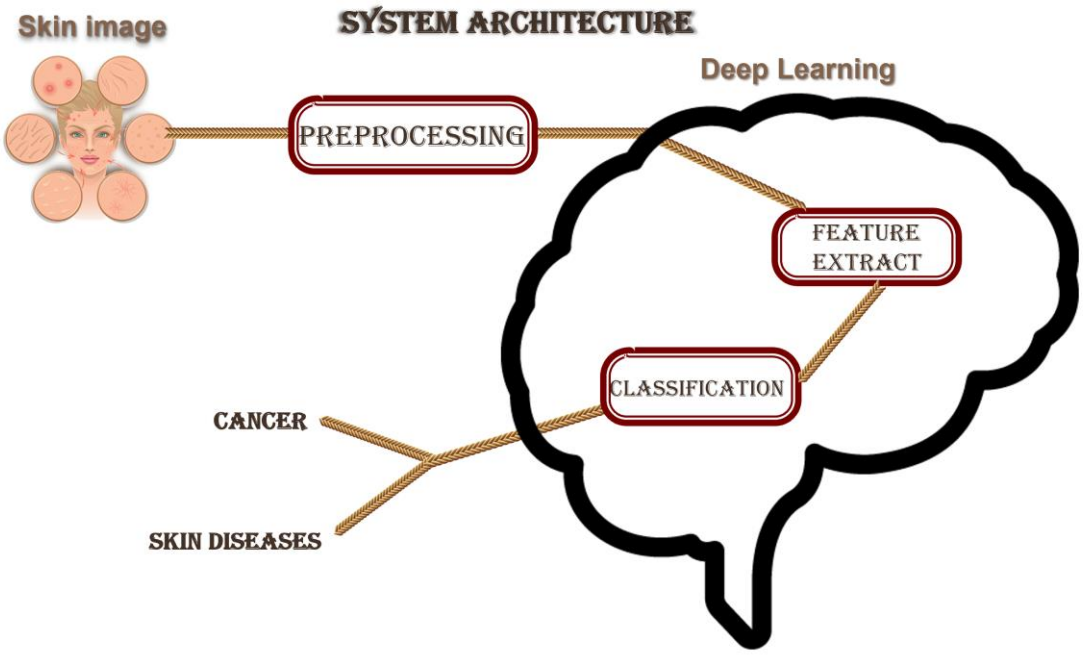

Fig. 3.1 System Architecture

The initial module, Preprocessing, is tasked with preparing raw dermatological images for subsequent analysis. This preparatory process encompasses critical steps such as noise reduction, normalization, watermark removal, and data augmentation. These procedures are fundamental in enhancing the quality and variability of the input images, thereby ensuring that the ensuing feature extraction and classification stages operate on high-caliber data. Effective preprocessing is paramount as it establishes the foundation for the accurate and reliable extraction and classification of features. The rigorous preprocessing phase mitigates potential artifacts and variations that could otherwise compromise the system's performance.[3]

The subsequent module, Feature Extraction, is dedicated to extracting salient features from the preprocessed images using sophisticated deep learning algorithms. This process entails capturing essential characteristics and intricate patterns within skin images that are indicative of various dermatological conditions. Advanced techniques, such as Convolutional Neural Networks (CNNs), are deployed to automatically extract hierarchical and discriminative features that are critical for precise classification. By identifying these features, the system can adeptly differentiate between a diverse array of skin diseases.[1] The feature extraction process is thus crucial for transforming raw image data into a meaningful and high-dimensional representation that can be effectively utilized in the classification phase.

The culminating module, Classification, leverages the extracted features to categorize dermatological images into specific disease classes. This module employs deep learning models that have been meticulously trained on annotated datasets to predict whether an input image corresponds to cancerous conditions or other dermatological diseases. The classification process is structured hierarchically to augment diagnostic accuracy and efficiency. Initially, a binary classification algorithm is utilized to differentiate between cancerous and non-cancerous conditions. Following this initial categorization, a second level of classification is executed. For images classified as non-cancerous skin diseases, a multi-class classification approach is employed to further categorize these conditions into specific diseases such as eczema, seborrheic keratoses, Melanocytic Nevi, or other disorders. Conversely, images identified as cancerous undergo an additional binary classification step to distinguish between melanoma and basal cell carcinoma (BCC).[21]

This hierarchical classification methodology not only enhances the system's precision and diagnostic granularity but also aids medical professionals in making informed clinical decisions.[18] Using the power of deep learning, the system architecture effectively processes dermatological images and provides nuanced, reliable, and actionable diagnostic support. This comprehensive approach ensures that the system can deliver high-fidelity diagnostic outcomes, thereby contributing significantly to the field of dermatological diagnostics as shown in ***Fig. 3.2***

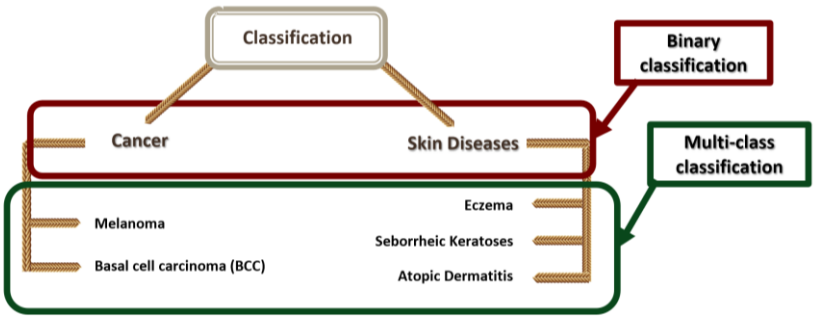

Fig. 3.2 Hierarchal Classification Architecture

3.3 A detailed description of all the functions in the system

1. Preprocessing

Purpose:

The preprocessing function prepares raw dermatological images for further analysis by enhancing their quality and consistency.

Process:

- **Image Rescale:** Adjusts the size of images to a standard scale for uniformity across the dataset.
- **Image Reshape:** Reshapes images to fit the input requirements of the deep learning model.
- **Splitting Data (Train 80%, Validate 20%):** Divides the dataset into training and validation sets to ensure robust model evaluation.
- **Weight Distribution:** Balances the dataset by adjusting the weights of different classes to handle class imbalance.
- **Noise Reduction:** Applies filtering techniques to eliminate random variations in pixel intensity that may obscure important features.
- **Watermark Removal:** Identifies and removes any superimposed text or logos that could interfere with feature extraction.
- **Normalization:** Adjusts pixel intensity values to a common scale, reducing illumination variations and improving the model's convergence during training.
- **Data Augmentation:** Implements transformations such as rotation, flipping, zooming, and cropping to increase the diversity of the training dataset, enhancing the robustness of the deep learning model.

Role:

Preprocessing ensures that the input images are standardized and of high quality, which is crucial for the accuracy of subsequent feature extraction and classification processes.

2. Feature Extraction

Purpose:

The feature extraction function identifies and extracts essential features from preprocessed images that are indicative of various dermatological conditions.

Process:

- **Convolutional Neural Networks (CNNs):** Utilize layers of convolution, pooling, and activation functions to automatically detect and learn hierarchical features from the images.
- **Hierarchical Feature Extraction:** Captures low-level features such as edges and textures in the initial layers, and higher-level features such as patterns and shapes in the deeper layers.

Role:

Feature extraction transforms preprocessed images into high-dimensional feature vectors that encapsulate critical characteristics necessary for accurate classification.

3. Classification

Purpose:

The classification function categorizes dermatological images into specific disease classes based on the extracted features.

Process:

- **Hierarchical Classification Approach:**
- **First Level - Binary Classification:** Differentiates between cancerous and non-cancerous conditions using a binary classifier.
- **Second Level - Multi-class Classification for Non-cancerous Conditions:** Further classifies non-cancerous conditions into specific diseases such as eczema, seborrheic keratoses, Melanocytic Nevi, and other disorders.
- **Second Level - Binary Classification for Cancerous Conditions:** Distinguishes between melanoma and basal cell carcinoma (BCC) for images classified as cancerous in the first level.
- **Multi Class Single Classification Approach**: This approach involves a direct multi-class classification method, categorizing images into five specific disease classes in a single step. The disease classes include Eczema, Melanoma, Basal Cell Carcinoma (BCC), Melanocytic Nevi (NV), and Seborrheic Keratoses along with other benign tumors. By simplifying the classification process, this approach enables straightforward categorization of dermatological conditions without the need for hierarchical decision-making.

Role:

Classification provides a precise diagnosis by categorizing images into specific disease classes, aiding medical professionals in making informed clinical decisions.

4. User Interface

Purpose:

The user interface function facilitates easy interaction between healthcare professionals and the system.

Process:

- **Input Interface**: Allows users to upload and manage dermatological images.
- **Diagnostic Output**: Displays classification results along with relevant diagnostic information and confidence scores.
- **Integration Features**: Supports integration with electronic health records (EHR) systems and other medical software for seamless workflow integration.

Role:

The user interface ensures that the system is user-friendly and accessible, enabling healthcare professionals to utilize the diagnostic capabilities effectively in their daily practice.

By organizing and detailing each function in this manner, the comprehensive understanding of the system's capabilities and the processes involved in each stage of dermatological image analysis and diagnosis are enhanced.

3.4 A detailed description of all the techniques and algorithms implemented

1. Preprocessing Techniques

Image Rescale:

- **Purpose**: To ensure all images are of a uniform size.
- **Technique**: This process involves resizing images to a standard dimension to maintain consistency in input data, which is critical for the performance and convergence of deep learning models.

Image Reshape:

- **Purpose**: To adjust the shape of images to match the input requirements of the models.
- **Technique**: Images are reshaped to fit the expected input dimensions of the neural networks, ensuring compatibility and optimal processing.

Splitting Data (Train 80%, Validate 10%, Test 10%):

- **Purpose**: To create a training set and a validation set.
- **Technique**: The dataset is divided into 80% for training the model, 10% for testing its performance, and 10% for validation. This split helps in evaluating the model's generalizability and ensures robust performance assessment.

Weight Distribution:

- **Purpose**: To handle class imbalance.
- **Technique**: This involves adjusting the weights of different classes in the training process to ensure that the model does not become biased towards any class due to uneven class distribution.

Noise Reduction:

- **Purpose**: To enhance image quality by removing unwanted noise.
- **Technique**: Filtering techniques are applied to reduce random variations in pixel intensity, which can obscure important features and negatively impact model performance.

Watermark Removal:

- **Purpose**: To eliminate superimposed text or logos that can interfere with feature extraction.
- **Technique**: Specific algorithms are used to detect and remove watermarks, ensuring that the image content remains unaffected and clear for analysis.

Data Augmentation:

- **Purpose:** To increase the diversity of the training dataset.
- **Technique:** Various transformations such as rotation, flipping, zooming, and cropping are applied to images. This helps in making the model robust to variations and improves its generalization ability.

2. Models and Algorithms

Convolutional Neural Networks (CNNs):

- **Structure**: Consists of several convolutional layers with increasing filter sizes, each followed by a max-pooling layer. The model ends with a global average pooling layer, followed by dense layers and a softmax.
- **Purpose**: To automatically detect and learn hierarchical features from images.

- **Technique**: CNNs use layers of convolution, pooling, and activation functions to capture essential characteristics and patterns within the images, making them highly effective for image classification tasks.[1]

AlexNet:

- **Structure**: Consists of 8 layers: 5 convolutional layers, 2 fully connected layers, and an output layer.
- **Purpose**: Designed for large-scale image recognition.
- **Technique**: Utilizes ReLU activation, dropout layers for regularization, and max-pooling layers to reduce spatial dimensions, enhancing feature extraction and reducing overfitting.[26]

EfficientNet:

- **Structure**: Comprises three layers: an EfficientNetB0 base model, a global average pooling layer, and an output layer.
- **Purpose**: Balances model accuracy and efficiency.
- **Technique**: Uses compound scaling to uniformly scale depth, width, and resolution, optimizing both performance and computational cost.[28]

Inception:

- **Structure**: Consists of two Inception modules, a flatten layer, a dense layer with ReLU activation and L2 regularization, a dropout layer, and an output layer.
- **Purpose**: Enhances model's ability to capture features at multiple scales.
- **Technique**: Inception modules use parallel convolutions with different filter sizes, concatenating their outputs to capture a variety of feature types.[12]

MobileNetV2:

- **Structure**: Comprises 53 layers, incorporating inverted residual blocks, depth wise separable convolutions, and linear bottlenecks.
- **Purpose**: Optimized for mobile and embedded vision applications.
- **Technique**: Utilizes lightweight convolutions and efficient layer connections to reduce computational requirements while maintaining high accuracy.[10]

MobileNetV3:

- **Structure**: Consists of a series of layers including initial convolutional layers, bottleneck layers, and specialized activation functions.

- **Purpose**: Designed to achieve high performance with minimal computational resources, particularly for mobile and edge devices.
- **Technique**: Combines the benefits of MobileNetV2 with additional optimizations such as squeeze-and-excitation modules and a modified swish activation function to enhance efficiency and accuracy.[27]

ResNet50:

- **Structure**: Contains 50 layers, utilizing residual blocks with skip connections to allow for deeper networks without vanishing gradient issues.
- **Purpose**: Aims to simplify the training of very deep networks.
- **Technique**: Uses identity shortcuts to jump over some layers, addressing the degradation problem by allowing gradient flows directly through the network layers.[12]

Each of these models and preprocessing techniques plays a vital role in the overall system, ensuring high accuracy and reliability in the detection and classification of dermatological conditions. The combination of robust preprocessing and sophisticated deep learning models allows the system to deliver precise and actionable diagnostic insights.

Chapter 4

System Implementation and Results

4.1 Datasets

Dataset 1: Skin Diseases Image Dataset

Overview

The Skin Diseases Image Dataset is a comprehensive collection of skin disease images, intended for use in research and development of diagnostic tools. This dataset provides a wide range of skin disease images to enhance model training diversity and robustness.

Specifications

- **Number of Images**: 3,668
- **Number of Categories**: 10 different skin diseases
- **Image Resolution**: High-resolution images suitable for detailed analysis
- **Format**: JPEG
- **Annotations**: Each image is classified under one of the following categories of skin diseases

Categories

The dataset encompasses images representing the following skin conditions:

- Eczema
- Warts Molluscum and other Viral Infections
- Melanoma
- Atopic Dermatitis
- Basal Cell Carcinoma (BCC)
- Melanocytic Nevi (NV)
- Benign Keratosis-like Lesions (BKL)
- Psoriasis Lichen Planus and related diseases
- Seborrheic Keratoses and other Benign Tumors
- Tinea Ringworm Candidiasis and other Fungal Infections

Usage

This dataset is employed to enhance the accuracy and reliability of machine learning models in identifying and diagnosing various skin diseases. The variety in the dataset helps in improving model generalization across different types of skin conditions.[13]

Dataset 2: DermNet Dataset

Overview

The DermNet dataset is a collection of images sourced from the DermNet Skin Disease Atlas. It contains a comprehensive set of images representing various skin conditions, used primarily for the development and training of machine learning models for skin disease classification.

Specifications

- **Number of Images**: 23,314
- **Number of Categories**: 23 different skin diseases
- **Image Resolution**: Varies, but typically high-resolution images suitable for medical diagnosis
- **Format**: JPEG
- **Annotations**: Images are labeled with the name of the skin condition they represent

Categories

The dataset includes images categorized under various skin diseases such as:

- Acne and Rosacea
- Fungal Infections
- Viral Infections
- Pigmentation Disorders
- Benign Tumors
- Malignant Tumors
- Hair Diseases
- Nail Diseases

Usage

This dataset is used for training and validating machine learning models in dermatological diagnostics. It aids in building algorithms capable of identifying skin diseases from images, which can assist dermatologists in clinical settings.[5]

Summary

Both datasets are crucial for the development of AI-driven diagnostic tools in dermatology. They provide a rich source of labeled images that help in training, validating, and testing machine learning models aimed at skin disease detection and classification. These datasets contribute to advancing dermatological research and improving clinical decision-making through enhanced diagnostic capabilities.[5][13]

4.2 Description of software programs used

Flutter: A UI toolkit developed by Google for building natively compiled applications for mobile, web, and desktop from a single codebase.

Google Colab: Utilized for running code in the Python language. It provides a cloud-based environment that allows for executing Python scripts without the need for local setup, offering powerful computational resources and seamless integration with Google Drive.

Visual Studio: Some parts of the project are run locally on laptops. This involves setting up the necessary environment and dependencies on personal machines to execute and test code efficiently.

4.3 Experimental and Results

We initiated an analysis on a dataset comprising 10 classes (8 skin diseases and 2 cancer types) using a Convolutional Neural Network (CNN) model. No preprocessing techniques were applied. The objective was to perform binary classification to distinguish between skin diseases and cancer, and the following results were obtained:

Subsequently, we evaluated five models (CNN, AlexNet, Inception, EfficientNet, and MobileNetV2) on the same dataset but only taking five classes: three skin diseases (Eczema, Seborrheic Keratoses, and Atopic Dermatitis) and two cancer types (BCC and Melanoma). Preprocessing techniques, including image rescaling, image reshaping, and data splitting (70% training and 30% validation), were applied. ***Table 4.1*** shows the results.

Table 4.1 Binary Classification using CNN

Input Layer	Output Layer	Hidden Layers	Image Size	Batch Size	Learning Rate	Epochs	Accuracy
ReLU	Sigmoid	32, 64, 128	32	32	0.001	20	90.36%
LeakyReLU (alpha=0.3)	Sigmoid	32, 64, 128	64	32	0.001	20	89.80%
ReLU	Sigmoid	64, 128, 256	64	32	0.001	13	89.00%
LeakyReLU (alpha=0.2)	Sigmoid	64, 128, 256	32	32	0.001	20	89.79%
ReLU	Sigmoid	32, 64, 128	64	32	0.001	20	88.65%

CNN Results:

- Binary

Table 4.2 summarizes the binary classification performance using CNN on 5 classes from dataset1 without preprocessing, showing that a model with 4 layers, LeakyReLU (alpha=0.2), a learning rate of 0.0001, 30 epochs, and a batch size of 64 achieved the highest accuracy of 96.79% with a validation loss of 0.25.

Table 4.2 Binary Classification using CNN (5 Classes)

Layers	Activation	Learning Rate	Epochs	Batch Size	Accuracy	Val loss
4	LeakyReLU (alpha=0.2)	0.0001	30	64	96.79%	0.25
4	LeakyReLU (alpha=0.2)	0.0001	12	32	96.39%	0.12
3	LeakyReLU (alpha=0.2)	0.001	12	32	96.23%	0.15
4	ReLU	0.0001	30	64	95.55%	0.22

- Skin

Table 4.3 details the performance of a CNN for skin classification into 3 classes without preprocessing on dataset1, showing that the best accuracy of 69.39% with a validation loss of 0.8516 was achieved using 7 layers, ReLU activation, a learning rate of 0.00001, 150 epochs, and a batch size of 32.

Table 4.3 Skin Classification using CNN

Img Size	Layers	Activation	Learning Rate	Epochs	Batch Size	Accuracy	Val loss
224	7 Layers	Relu	0.00001	150	32	69.39%	0.8516
224	7 Layers	Relu	0.00001	100	32	68.95%	0.7609
224	7 Layers	Relu	0.00001	30	32	67.68%	0.76
224	7 Layers	Relu	0.00001	30	16	65.65%	0.7785
224	6 Layers	Relu	0.00001	30	32	65.53%	0.81
224	5 Layers	Relu	0.00001	30	32	59.76%	0.9

- Cancer

Table 4.4 outlines the performance of a CNN for cancer classification into 2 classes without preprocessing on dataset1, demonstrating that the highest accuracy of 98.45% with a validation loss of 0.048 was achieved using 6 layers, LeakyReLU (alpha=0.2), a learning rate of 0.0001, 30 epochs, and a batch size of 64.

Table 4.4 Cancer Classification using CNN

Layers	Activation	Learning Rate	Epochs	Batch Size	Accuracy	Val loss
6 Layers	LeakyReLU (alpha=0.2)	0.0001	30	64	98.45%	0.048
7 Layers	Relu	0.0001	50	16	98.41%	0.1549
7 Layers	Relu	0.0001	25	16	97.98%	0.0732
7 Layers	Relu	0.00001	15	8	96.39%	0.1018

AlexNet Results:

- Binary

Table 4.5 presents the results of binary classification using AlexNet on 5 classes from dataset1 without preprocessing, indicating that the highest accuracy of 98.18% with a loss of 0.4478 was achieved using an image size of 280, batch size of 32, learning rate of 0.00001, and 50 epochs.

Table 4.5 Binary Classification using AlexNet

IMGSIZE	Batch Size	Lr	Epochs	Accuracy	Loss
280	32	0.00001	50	98.18 %	0.4478
280	32	0.00001	30	98.04 %	0.4672
224	32	0.00001	30	97.69 %	0.4511
300	32	0.00001	15	94.80%	0.6324
256	32	0.000001	15	88.08 %	0.5624

- Skin

We observed that the model exhibited overfitting, as indicated by the following results across various configurations:

Table 4.6 presents results from skin classification experiments using varying image sizes, batch sizes, learning rates, and epochs, achieving accuracies ranging from 64.37% to 71.13% with corresponding loss values.

Table 4.6 Skin Classification using AlexNet

IMGSIZE	Batch Size	Lr	Epochs	Accuracy	Loss
310	32	0.00001	30	71.13%	1.1091
350	32	0.00001	20	70.50%	1.0519
300	32	0.00001	20	69.67%	0.9334
224	32	0.0001	15	66.32%	1.2294
224	32	0.000001	15	64.37%	0.8136

- Cancer

Table 4.7 summarizes cancer classification results using AlexNet with different image sizes, batch sizes, learning rates, and epochs, achieving accuracies ranging from 95.51% to 98.04% with corresponding loss values.

Table 4.7 Cancer Classification using AlexNet

IMGSIZE	Batch Size	Lr	Epochs	Accuracy	Loss
390	64	0.00001	50	98.04%	0.0891
390	64	0.00001	20	97.99%	0.0647
224	32	0.00001	30	97.37%	0.0847
256	32	0.00001	10	97.21%	0.0787
224	64	0.00001	30	96.96%	0.0921
224	32	0.0001	20	96.23%	0.1185
256	64	0.00001	10	95.51%	0.1118

EfficientNet Results:

- Binary

Table 4.8 presents binary classification results using EfficientNet with varying image sizes, batch sizes, learning rates, and epochs, achieving accuracies ranging from 88.52% to 99.73%.

Table 4.8 Binary Classification using EfficientNet

Image Size	Batch Size	Learn. Rate	Epochs	Accuracy
200	16	0.001	6	99.73%
180	16	0.001	10	98.40%
150	16	0.0001	15	97.15%
60	32	0.001	15	96.62%
100	16	0.001	5	94.88%
180	16	0.00001	10	91.73%
120	32	0.00001	10	88.52%

- Skin

Table 4.9 summarizes skin classification results using EfficientNet for 3 classes with various configurations of image size, batch size, learning rate, and epochs, achieving accuracies ranging from 52.46% to 60.42%.

Table 4.9 Skin Classification using EfficientNet

Image Size	Batch Size	Learn. Rate	Epochs	Accuracy
200	8	0.001	10	60.42%
200	8	0.0001	20	58.43%
200	16	0.00001	20	55.71%
300	4	0.0001	12	54.55%

- Cancer

Table 4.10 outlines cancer classification results using EfficientNet for 2 classes without preprocessing on dataset1, showing accuracies ranging from 78.41% to 89.86% across different configurations of image size, batch size, learning rate, and epochs.

Table 4.10 Cancer Classification using EfficientNet

Image Size	Batch Size	Learn. Rate	Epochs	Accuracy
300	4	0.0001	20	89.86%
200	8	0.0001	8	88.24%
200	16	0.0001	15	85.22%
180	4	0.0001	15	82.89%
200	8	0.0001	20	81.81%

Inception Results:

- Binary

Table 4.11 presents results for binary classification using Inception with 5 classes, without preprocessing on dataset1. It shows accuracy ranging from 87.00% to 99.00% across different configurations of image size, learning rate, batch size, and epochs.

Table 4.11 Binary Classification using Inception

Image Size	Learning Rate	Batch Size	Epochs	Accuracy
200	0.001	8	6	99.00%
32	0.001	32	13	97.00%
200	0.001	8	6	92.00%
188	0.001	8	6	91.00%
194	0.001	8	6	89.00%
224	0.001	8	6	87.00%

- Skin

Table. 4.12 outlines skin classification results using Inception for 3 classes, without preprocessing on dataset1. Accuracy varies from 38.00% to 50.00% with different image sizes, learning rates, batch sizes, and epochs.

Table 4.12 Skin Classification using Inception

Image Size	Learning Rate	Batch Size	Epochs	Accuracy
200	0.0001	8	6	50.00%
176	0.0001	8	6	38.00%
200	0.001	8	6	38.00%
200	0.0001	16	6	38.00%

- Cancer

Table. 4.13 summarizes cancer classification results using Inception for 2 classes, without preprocessing on dataset1. Accuracy ranges from 58.00% to 93.00% across various configurations of image size, learning rate, batch size, and epochs.

Table 4.13 Cancer Classification using Inception

Image Size	Learning Rate	Batch Size	Epochs	Accuracy
32	0.001	32	13	93%
224	0.001	8	6	80.00%
200	0.001	8	6	79.00%
248	0.001	8	6	65.00%
200	0.0001	8	6	58.00%

MobileNet(V2) Results:

- Binary

Table 4.14 shows binary classification using MobileNet(V2) on 5 classes from dataset1 without preprocessing achieved the highest validation accuracy of 95.88% with a training accuracy of 97.71%, using a learning rate of 0.00001, batch size of 32, 30 epochs, binary loss, and the Adam optimizer.

Table 4.14 Binary Classification using MobileNet(V2)

Lr	Batch	epochs	loss	optimizer	Train Acc	Val Acc	Train Loss	Val Loss
0.00001	32	30	binary	Adam	97.71%	95.88%	0.0638	0.1234
0.00001	32	20	binary	Adam	97.60%	95.76%	0.0681	0.1394

- Skin

Table 4.15 shows skin classification using MobileNet(V2) on 3 classes from dataset1 without preprocessing showed the highest training accuracy of 98.65% but a lower validation accuracy of 66.67%, using a learning rate of 0.00001, batch size of 32, 30 epochs, sparse loss, and the Adam optimizer.

Table 4.15 Skin Classification using MobileNet(V2)

Lr	batch	epochs	loss	optimizer	Train Acc	Val Acc	Train Loss	Val Loss
0.00001	32	30	sparse	Adam	81.43%	66.67%	0.4931	0.7925
0.00001	32	30	sparse	Adam	94.95%	64.44%	0.1542	1.1106
0.0001	32	30	sparse	Adam	98.65%	64.30%	0.0449	2.1188
0.0001	32	30	sparse	Adam	97.42%	62.55%	0.0685	1.6345

- Cancer

Table 4.16 shows **c**ancer classification using MobileNet(V2) on 2 classes from dataset1 without preprocessing achieved the highest validation accuracy of 96.85% with a training accuracy of 97.85%, using a learning rate of 0.00001, batch size of 32, 20 epochs, binary loss, and the Adam optimizer.

Table 4.16 Cancer Classification using MobileNet(V2)

Lr	batch	epochs	loss	optimizer	Train Acc	Val Acc	Train Loss	Val Loss
0.00001	32	20	binary	Adam	97.85%	96.85%	0.061	0.085
0.00001	32	20	binary	Adam	99.30%	96.80%	0.0211	0.1162

Our exploration of optimal models using hierarchical classification identified EfficientNet (99.73% accuracy) for binary classification, AlexNet (71.13% accuracy) for skin cancer, and a 6-layer ReLU CNN (98.45% accuracy) for cancer, emphasizing task-specific model selection. Following the success of our binary and cancer classification models, we aimed to enhance skin cancer classification

accuracy through various preprocessing and data augmentation techniques. These strategies included horizontal flipping to reduce bias, shear and zoom range augmentation to improve data diversity and robustness, image rescaling for consistent input sizes, and brightness adjustments to simulate real-world lighting variations. We also used a validation split for model evaluation. Callbacks were employed for learning rate reduction, model checkpointing, and early stopping to prevent overfitting and optimize training efficiency. The following trials, conducted on a customized CNN model, used the same three classes: Eczema, Seborrheic Keratoses, and Atopic Dermatitis:

Using a mixed dataset consisting of our old and new datasets, including the DermNet dataset, we combined them. We took one class (atopic dermatitis) from the old dataset and the same two classes from the new dataset (DermNet) , but only for the skin dataset (the cancer dataset remains unchanged). The data is now more balanced, and the pictures are of higher quality. We experimented with four distinct models AlexNet, MobileNet V2 , MobileNet V3 and Inception. Shown in ***Table 4.17***

Table 4.17 Skin Classification using CNN

Img Size	Batch Size	Lr	Epochs	Layers	Accuracy	Loss
224	32	0.0001	20	7Layers(16,32,64,128,256,256,512) Relu	70%	0.8464
300	32	0.0001	30	7Layers(16,32,64,128,256,256,512) Relu	68.34%	0.8465
224	32	0.0001	30	7Layers(16,32,64,128,256,512,512) Relu	68%	0.8093
224	32	0.0001	20	7Layers(16,32,64,128,256,256,512) LeakyRelu (alpha=0.2)	66.60%	0.8537
250	8	0.00001	100	7Layers(16,32,64,128,256,256,512) Relu	64.80%	0.8321
224	64	0.00001	20	7Layers(16,32,64,128,256,256,512) Relu	61%	0.8879
224	32	0.00001	20	7Layers(16,32,64,128,256,256,512) LeakyRelu (alpha=0.2)	59.90%	0.8813

- AlexNet:

- IMG_SIZE = 224, Batch_Size = 32, Learing_Rate = 0.0001, Epochs = 30
- preprocessing techniques: shuffling, rescaling, shearing, zooming, horizontal flipping, adjusting brightness, validation split, and computing class weights based on class imbalance.

Table 4.18 shows the results of skin classification using AlexNet on 3 classes from a combination of 2 datasets with various preprocessing techniques, where the highest validation accuracy of 72.30% was achieved using class weights to address class imbalance.

Table 4.18 Skin Classification using AlexNet

Technique	Parameter Setting	Validation Accuracy
Shuffling Validation Data	shuffle=True	72.20%
Shuffling Validation Data	shuffle=False	69.00%
Validation Split	validation_split=0.3	72.20%
Validation Split	validation_split=0.2	68.60%
Class Weight	class_weight=False	72.20%
Class Weight	class_weight=True	72.30%

- MobileNet(V2):

Preprocessing Techniques: StandardScaler, train_test_split, ImageDataGenerator

Table 4.19 summarizes the hyperparameters for training our skin disease detection model using MobileNet(V2) on 3 classes from combined datasets with preprocessing and transfer learning. We used the Adam optimizer with an initial learning rate of 0.01, reducing to 0.001, a batch size of 32, and trained for 25 epochs. The SparseCategoricalCrossentropy loss function was used. Early stopping with a patience of 10 epochs and ReduceLROnPlateau with a factor of 0.2 and patience of 3 epochs were implemented to prevent overfitting and manage learning rate adjustments.

Table 4.19 Skin Classification using MobileNet(V2)

Hyperparameter	**Value**
Optimizer	Adam
Learning Rate	0.001
Batch Size	32
Epochs	25
Loss Function	SparseCategoricalCrossentropy
Early Stopping Patience	10
ReduceLROnPlateau Factor	0.2
ReduceLROnPlateau Patience	3
Initial Learning Rate (LearningRateScheduler)	0.01

Table 4.20 The accuracy of skin classification using MobileNet(V2) on 3 classes from a combination of 2 datasets with some simple preprocessing and transfer learning was 97.2% for the training set, 85.1% for the validation set, and 83.5% for the test set.

Table 4.20 Accuracy of Skin Classification using MobileNet(V2)

Metric	Training Set	Validation Set	Test Set
Accuracy	97.2%	85.1%	83.5%

Table 4.21 shows the loss of skin classification using MobileNet(V2) on 3 classes from a combination of 2 datasets with some simple preprocessing and transfer learning was 0.09 for the training set and 0.5 for the validation set.

Table 4.21 Loss of Skin Classification using MobileNet(V2)

Metric	Training Set	Validation Set
Loss	0.09	0.5

The plot shows the training and validation accuracy over 25 epochs, indicating that training accuracy steadily increases, while validation accuracy stabilizes around 85%, suggesting potential overfitting after early epochs as shown in ***Fig. 4.1***

The graph illustrates the model loss for both training and validation datasets over 25 epochs, showing a steady decrease in training loss and a stabilization in validation loss after an initial decline, indicating the model's learning progression and performance stability as shown in ***Fig. 4.1***

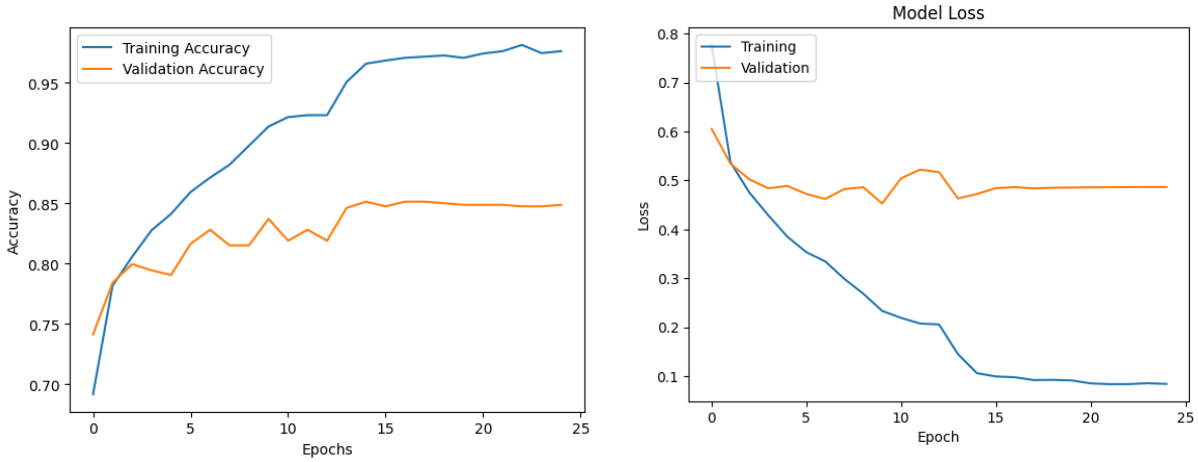

Fig. 4.1 Accuracy and loss of MobileNet(V2)

This confusion matrix shows the performance of a classification model on skin diseases, where the model accurately classified Eczema, Atopic Dermatitis, and Seborrheic Keratoses and other benign tumors with varying degrees of precision as shown in ***Fig. 4.2***

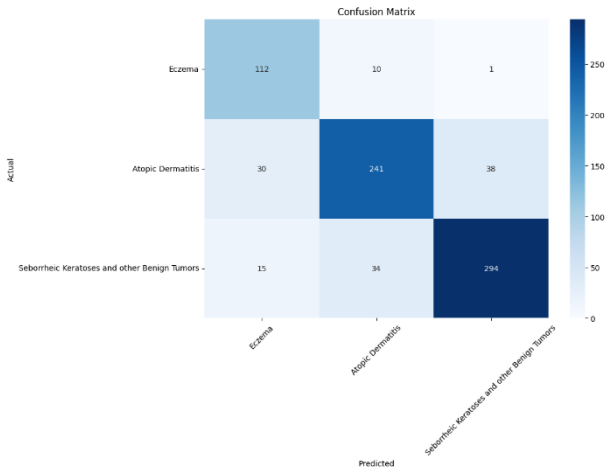

Fig. 4.2 Confusion Matrix of MobileNet(V2)

- MobileNet(V3):

Preprocessing Techniques: StandardScaler, train_test_split, ImageDataGenerator

The table outlines the hyperparameters used for training the skin disease detection model. The Adam optimizer was employed with a learning rate of 0.001. A batch size of 32 was chosen, and the model was trained for 25 epochs using the SparseCategoricalCrossentropy loss function. Early stopping was implemented with a patience of 10 epochs to prevent overfitting. The learning rate was dynamically reduced using ReduceLROnPlateau with a factor of 0.2 and a patience of 3 epochs. Additionally, the initial learning rate was set to 0.01 using a LearningRateScheduler to facilitate faster early-stage convergence as shown in ***Table 4.22***

Table 4.22 Skin Classification using MobileNet(V3)

Hyperparameter	Value
Optimizer	Adam
Learning Rate	0.001
Batch Size	32
Epochs	25
Loss Function	SparseCategoricalCrossentropy
Early Stopping Patience	10
ReduceLROnPlateau Factor	0.2
ReduceLROnPlateau Patience	3
Initial Learning Rate (LearningRateScheduler)	0.01

The table presents the accuracy of skin classification using MobileNet(V3) for three classes, trained on a combination of two datasets with simple pre-processing and transfer learning. The model achieved an accuracy of 96.40% on the training set, 85.12% on the validation set, and 84.90% on the test set, indicating a high level of performance, particularly during training, with slightly lower but consistent accuracy on validation and test sets as shown in ***Table 4.23***

Table 4.23 Accuracy of Skin Classification using MobileNet(V3)

Metric	Training Set	Validation Set	Test Set
Accuracy	96.40%	85.12%	84.90%

The table shows the loss values for skin classification using MobileNet(V3) on three classes, trained with a combination of two datasets using simple pre-processing and transfer learning. The loss on the training set is 0.1157, indicating a good fit to the training data, while the validation set shows a higher loss of 0.4136, suggesting some level of overfitting or the need for further model tuning as shown in ***Table 4.24***

Table 4.24 Loss of Skin Classification using MobileNet(V3)

Metric	Training Set	Validation Set
Loss	0.1157	0.4136

This accuracy plot illustrates the training and validation performance of a model over 35 epochs. The training accuracy consistently improves, reaching over 95%, while the validation accuracy stabilizes around 85%, model has good generalization but may benefit from further tuning to reduce overfitting as shown in ***Fig. 4.3***

This model loss plot shows the training and validation loss over 35 epochs. The training loss steadily decreases, indicating improved model performance on the training set, while the validation loss plateaus suggest that further training may not significantly enhance the model's generalization ability and could be an indication of overfitting as shown in ***Fig. 4.3***

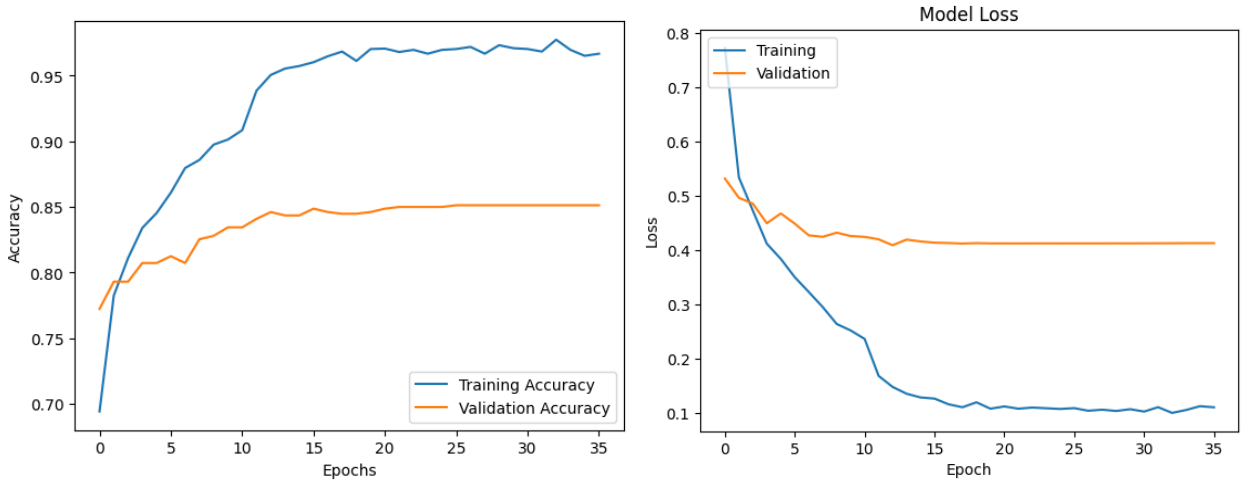

Fig. 4.3 Accuracy and loss of MobileNet(V3)

This confusion matrix shows the model's classification performance, with Eczema, Atopic Dermatitis, and Seborrheic Keratoses and other Benign Tumors having accuracies of 119, 241, and 298 respectively, while the misclassifications are minimal across the categories as shown in ***Fig. 4.4***

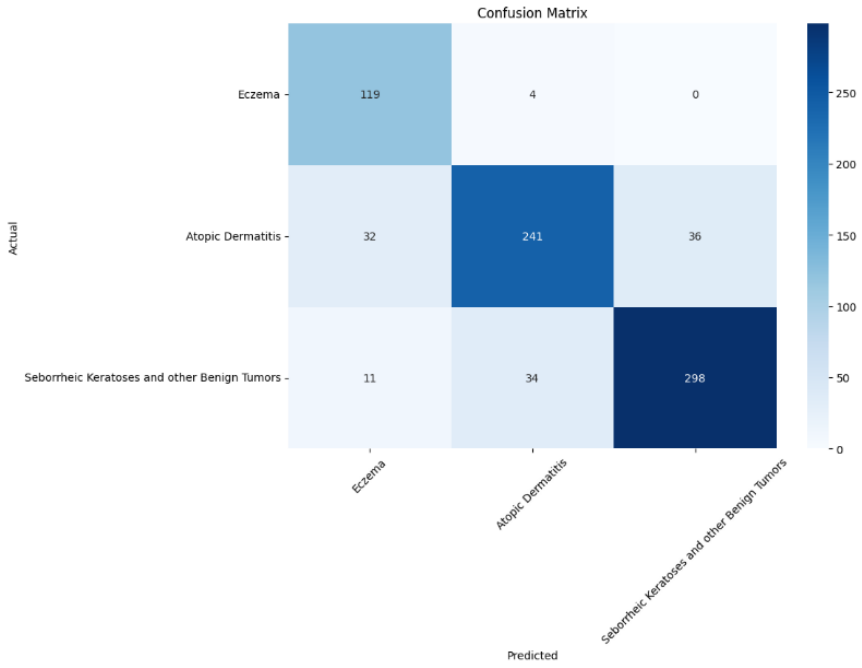

Fig. 4.4 Confusion Matrix of MobileNet(V3)

- Inception:

Table 4.25 summarizes skin classification results using the Inception model with varying image sizes, batch sizes, learning rates, and augmentation techniques, achieving validation accuracies ranging from 71% to 82%.

Table 4.25 Skin Classification using Inception

Img Size	Batch Size	Lr	Epochs	Rotation Range	Width Shift Range	Height Shift Range	Shear Range	Zoom Range	Val Acc
224	32	0.00001	10	0	0	0	0	0	82%
128	32	0.00001	10	0	0	0	0	0	78%
224	32	0.0001	10	0	0	0	0	0	76%
224	32	0.00001	10	20	0	0	0.2	0	73%
224	32	0.00001	10	0	0	0	0.2	0.2	71%

We employed image processing techniques to remove watermarks from images within the skin diseases dataset, saving the processed images exclusively for analysis. Despite applying Inception to the original dataset comprising three classes Eczema, Seborrheic Keratoses, and Atopic Dermatitis the resulting accuracy did not show improvement.

Table 4.26 outlines skin classification results using Inception for three classes after applying watermark removal and basic preprocessing on dataset1. The model was trained with an image size of 224, batch size of 32, learning rate of 0.00001, over 10 epochs, with augmentation parameters. Validation accuracy reached 57%.

Table 4.26 Skin Classification using Inception

Img Size	Batch Size	Lr	Epochs	Rotation Range	Width Shift Range	Height Shift Range	Shear Range	Zoom Range	Val Acc
224	32	0.00001	10	20	0	0	0.2	0	57%

We combined two classes from the new DermNet dataset (Eczema and Seborrheic Keratoses) with the class "Atopic Dermatitis" extracted from the watermark-removed dataset of skin diseases, resulting in a total of three classes. Using the Inception model on this integrated dataset named DermNet increased accuracy to 74%

Table 4.27 summarizes skin classification using Inception for three classes from a combined dataset with simple preprocessing and watermark removal, achieving a validation accuracy of 74% with parameters including an image size of 224, batch size of 32, learning rate of 0.00001, and augmentation settings.

Table 4.27 Skin Classification using Inception

Img Size	Batch Size	Lr	Epochs	Rotation Range	Width Shift Range	Height Shift Range	Shear Range	Zoom Range	Val Acc
224	32	0.00001	10	0	0	0	0.2	0.2	74%

We proceeded with the classification of skin images into three classes by combining data from our two datasets using MobileNetV3 with transfer learning. The data was split into 80% for training and 20% for validation. Data augmentation techniques, including horizontal flipping and brightness adjustment within the range of 0.8 to 1.2, were applied. Additionally, the first 10 layers of MobileNetV3 were frozen to facilitate more effective learning from the data.

Table 4.28 reports the accuracy of skin classification using MobileNetV3 for three classes from a combined dataset with simple preprocessing, employing transfer learning with the first 10 layers frozen. The model achieved training accuracy of 99.62%, validation accuracy of 90.17%, and test accuracy of 90.45% after training with an image size of 224, batch size of 32, learning rate of 0.00001, over 100 epochs.

Table 4.28 Accuracy of Skin Classification using MobileNet(V3)

Img size	Batch Size	Lr	Epochs	Train Accuracy	Val Accuracy	Test Accuracy
224	32	0.00001	100	99.62%	90.17%	90.45%%

So far Using Hierarchical Classification, the best model for Binary classification: EfficientNet (99.73% accuracy), the Best Model for Cancer: a 6-layer ReLU CNN (98.45% accuracy) and finally the best model for Skin classification: MobileNet(V3) with (90.45% accuracy).

Initially, EfficientNet and other models achieved 60-70% accuracy in skin classification using a hierarchical approach., so we tried another way called Multi Class Single Classification we used 5 classes from dataset1(Eczema, Melanoma, Basal Cell Carcinoma(BCC), Melanocytic Nevi (NV), Seborrheic Keratoses and other Benign Tumors). Using the basic EfficientNet and the SGD optimizer, we achieved 70% accuracy. Switching to the Adam optimizer increased the accuracy to 75%. Employing transfer learning further improved the accuracy to 85%. Adding two layers to the basic EfficientNet model increased the accuracy to 93%. Using EfficientNetV2B0, we achieved an accuracy of 98.05%. The hyperparameters for the model were as follows: data was split into training, validation, and test sets with a ratio of 80%:10%:10%, image size was 224, batch size was 16, and the number of epochs was 70.

Table 4.29 presents the accuracy and loss metrics for classification using EfficientNetV2B0 on a dataset consisting of five classes from dataset1.

Table 4.29 Accuracy and loss of EfficientNetV2B0

Metric	Training Set	Validation Set	Test Set
Accuracy	99.99%	97.94%	98.05%
Loss	0.065075	0.133585	0.133833

The plot shows the training and validation accuracy over 45 epochs. Both accuracies increase and converge to high values, suggesting good model performance. The training accuracy continues to improve slightly, while the validation accuracy stabilizes, indicating no significant overfitting, as shown in ***Fig. 4.5***

The plot shows the training and validation loss over 45 epochs, indicating that both losses decrease and converge to low values, suggesting good model performance and no overfitting as shown in ***Fig. 4.5***

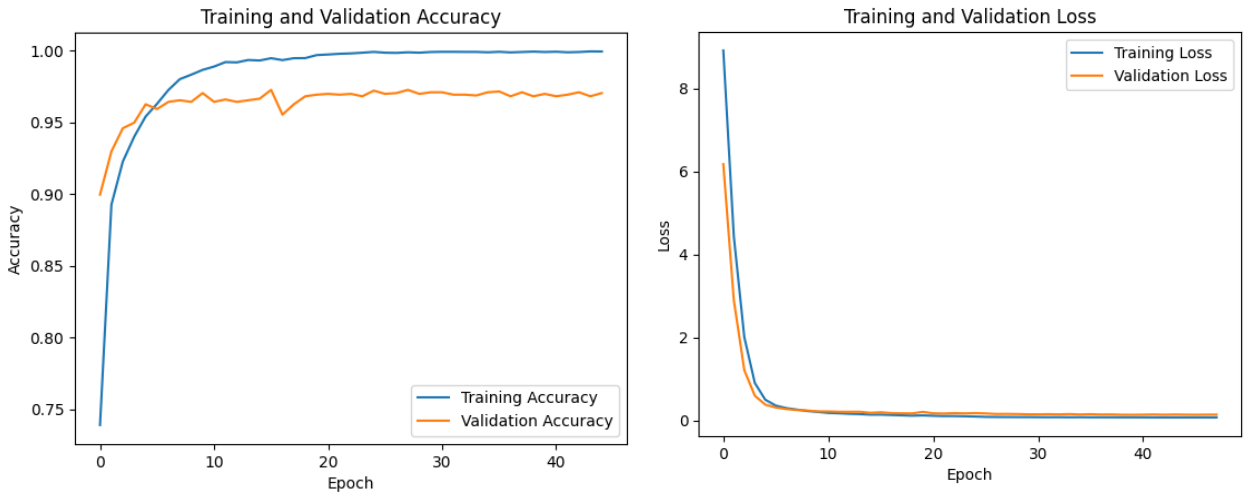

Fig. 4.5 Accuracy and loss of EfficientNetV2B0

The confusion matrix shows the performance of a classifier with true labels on the y-axis and predicted labels on the x-axis, highlighting correct and incorrect classifications across six classes as shown in ***Fig. 4.6***

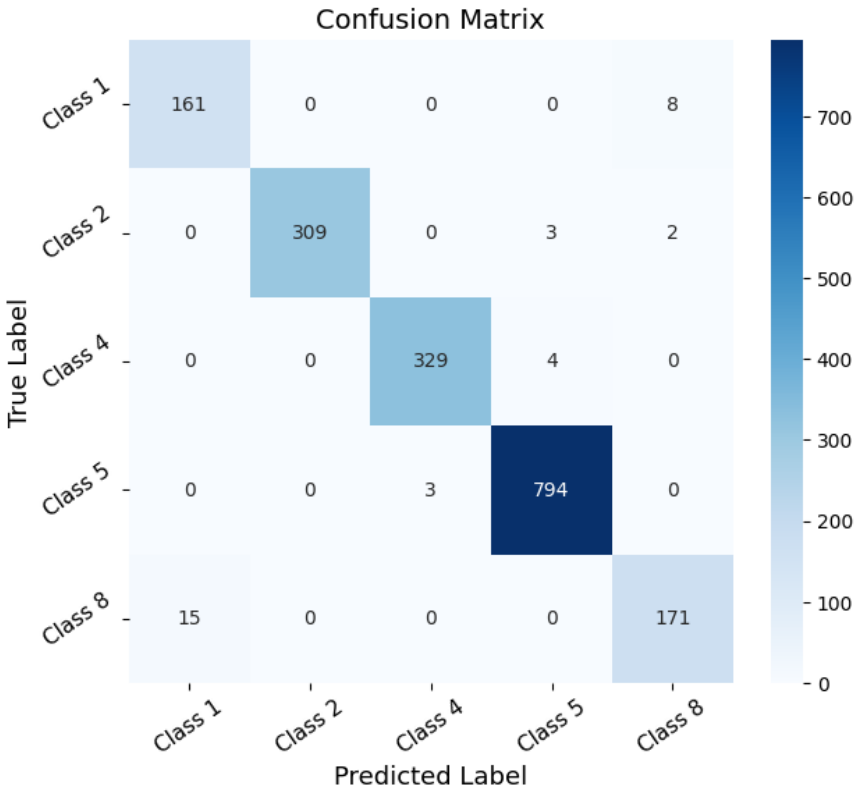

Fig. 4.6 Confusion Matrix of EfficientNetV2B0

We tried other models in Multi Class Single Classification for example ResNet50 and accuracy was 94.11% and tried MobileNet(V3) and accuracy was 97.13%

So far Using Multi Class Single Classification, the best model for classification: EfficientNet (98.05% accuracy).

Comparing results obtained with other researchers.

In our project, we achieved remarkable results for skin disease classification. For multi-class single classification, EfficientNet demonstrated an impressive accuracy of 98.05%, significantly outperforming the methodologies employed by other researchers. For binary classification within a hierarchical framework, EfficientNet again led with 99.73% accuracy, while a specialized 6-layer ReLU CNN achieved 98.45% accuracy for cancer classification. For overall skin classification, MobileNetV3 attained an accuracy of 90.45%. These results show a significant improvement over previous works, such as C.Gan et al. (92% using CNN, VIT, SLE), C.Viswantha Reddy Allugunti (88.83% using Decision Tree, Random Forest, Gradient Boosting Tree, CNN), C.Mostafiz Ahammed (93% using SVM, Decision Tree, KNN), C.Manu Goyal (90% using Inception, ResNet, VGG), and C.Mohamed et al. (93.20% using CNN, SVM, Google-Net, Resnet, VGG). Results in ***Table 4.30***

Table 4.30 Comparing results

Comparison	Accuracy
Other Researchers	88.83% - 93.20%
Our Work	98.05%

Chapter 5

Run the Application

To run the Application, Follow the steps below:

Step 1: Click on the Application as shown in ***Fig. 5.1.***

Step 2: Click on the Upload Button as shown in ***Fig. 5.1.***

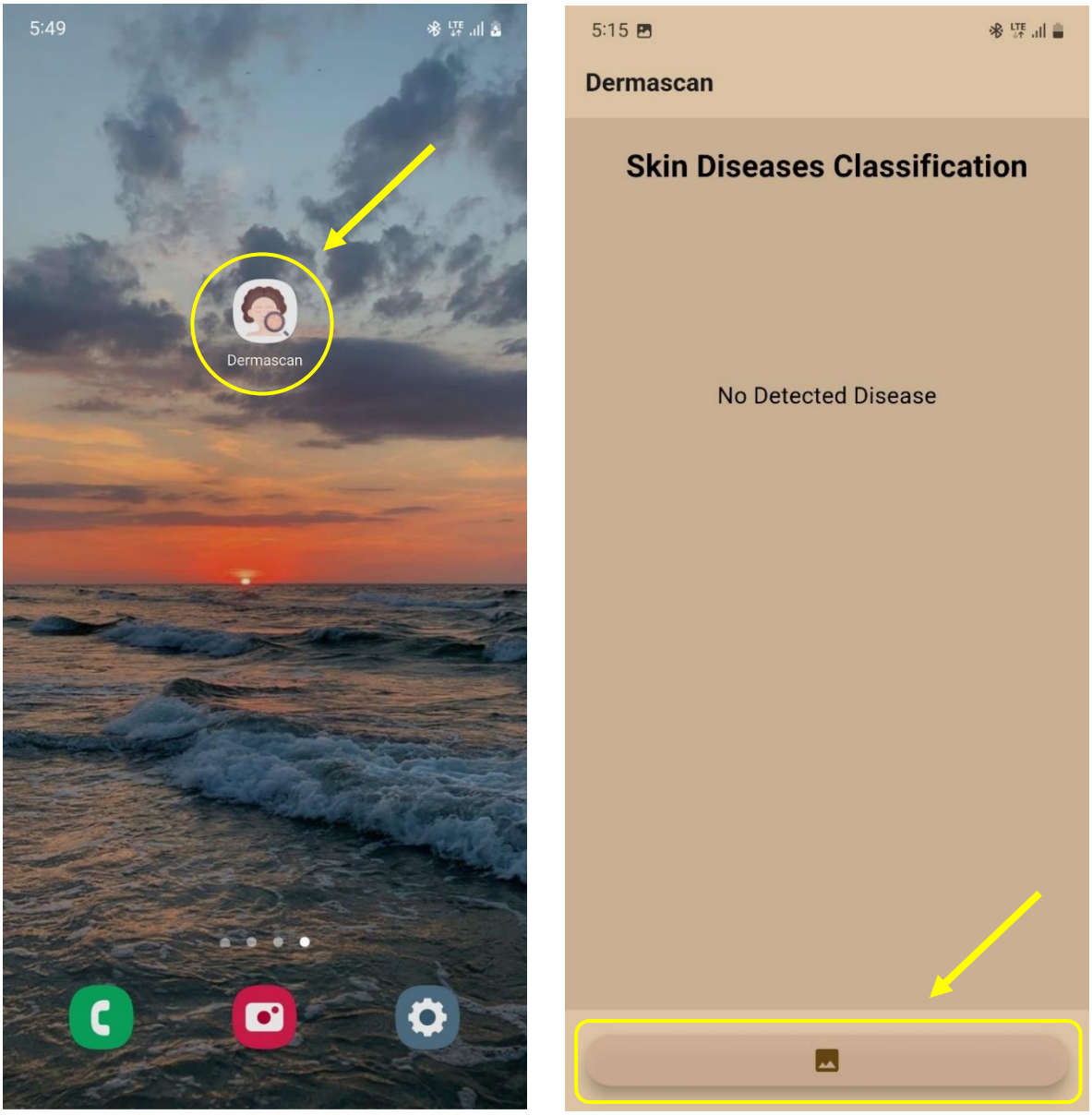

Fig. 5.1 Application At Homepage and Main Page

Step 3: Choose whether to **Take a Picture** using the camera or **Select Image** from the gallery, as shown in ***Fig. 5.2.***

Step 4: Select your desired image from the gallery, as shown in ***Fig. 5.2***

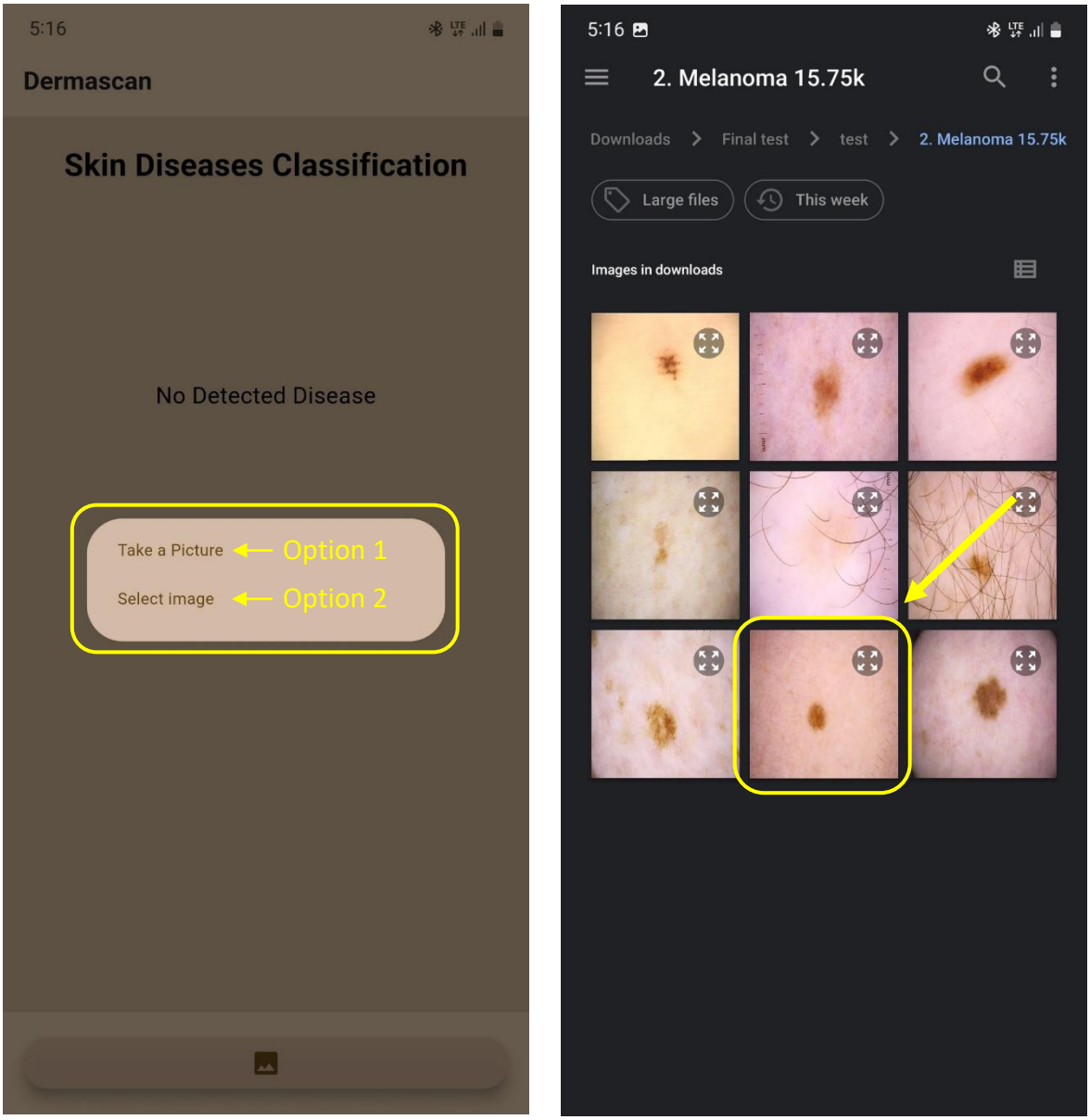

Fig. 5.2 Choosing image options and Choosing image from gallery

Output: Here you will obtain the results, as shown in ***Fig. 5.3***

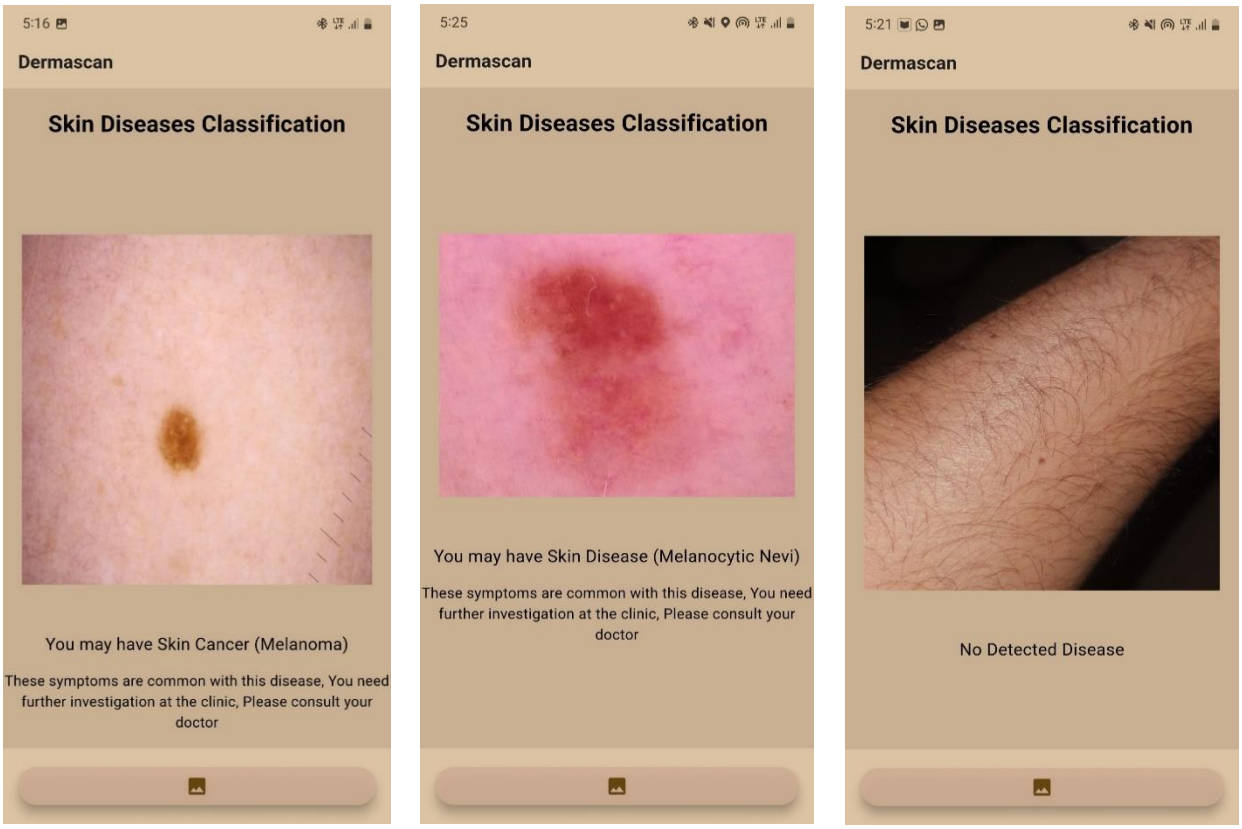

Fig. 5.3 Outputs of Application

Chapter 6
Conclusions and Future Work

6.1 Conclusion

This project presents a comprehensive skin disease detection system leveraging advanced deep learning techniques. The system architecture comprises preprocessing, feature extraction, and classification modules. Preprocessing enhances image quality through noise reduction, normalization, watermark removal, and data augmentation. Feature extraction employs Convolutional Neural Networks (CNNs) to capture hierarchical features indicative of dermatological conditions. The classification module utilizes a hierarchical approach: first, binary classification distinguishes between cancerous and non-cancerous conditions; then, further classifications identify specific diseases such as eczema, seborrheic keratoses, atopic dermatitis, or distinguish between melanoma and basal cell carcinoma. This robust system enhances diagnostic accuracy, aiding clinicians in making informed decisions, ultimately advancing dermatological diagnostics.

Despite the significant advancements demonstrated by the system, some misconceptions and limitations need addressing. For instance, the variability in image quality and lighting conditions can affect the system's performance, indicating a need for more sophisticated preprocessing techniques. Additionally, the imbalanced dataset remains a challenge, suggesting the necessity for more effective data augmentation methods or the inclusion of more diverse training data.

The importance of this project lies in its potential to significantly improve the accuracy and efficiency of skin disease diagnosis, thereby supporting healthcare professionals and enhancing patient outcomes. The practical implications include the possibility of integrating this system into clinical settings to assist dermatologists and other medical practitioners.

Addressing these issues will contribute to the ongoing improvement of dermatological diagnostics and support the broader application of deep learning techniques in medical image classification.

6.2 Future Work

To further enhance the performance and capabilities of this project, several avenues for future work can be explored:

1. Accuracy Improvement: Continue efforts to improve the accuracy of skin disease classification by experimenting with additional preprocessing techniques. This may include advanced augmentation methods, normalization techniques, and the use of synthetic data generation to balance the dataset further.

2. Cross-Platform Mobile Application: Expand the current Flutter application, which is presently available for Android, to support iOS as well. This will increase the accessibility of the app to a wider range of users. Additionally, improve the app's user interface and experience to ensure it is intuitive and easy to use for individuals of all ages.

3. User Experience Enhancements: Focus on making the mobile application more user-friendly. This includes simplifying navigation, adding voice assistance features, and incorporating multilingual support to cater to non-English speaking users. Implementing these features will help ensure the app is accessible to a broader demographic.

4. Model Optimization: Explore model compression techniques, such as pruning and quantization, to optimize the model for deployment on mobile devices. This will help in reducing the model's size and inference time, making it more efficient for real-time use.

5. Integration with Healthcare Systems: Develop APIs for integration with existing healthcare management systems to allow seamless sharing of diagnostic results with healthcare providers. This could facilitate faster decision-making and better patient management.

6. Real-World Testing and Validation: Conduct extensive real-world testing and validation of the model and mobile application in collaboration with healthcare institutions. Gather feedback from medical professionals and patients to refine the system further and ensure its reliability and effectiveness in clinical settings.

7. Advanced Neural Architectures: Experiment with more advanced neural architecture and techniques such as attention mechanisms, transformers, and generative adversarial networks (GANs) to improve the model's performance and robustness.

8. Continuous Learning and Adaptation: Implement continuous learning mechanisms where the model can be periodically updated with new data to adapt to evolving patterns in skin diseases and improve its diagnostic capabilities over time.

By pursuing these future work directions, we aim to enhance the accuracy, efficiency, and usability of our medical image classification system, ultimately contributing to better healthcare outcomes and accessibility.

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