EARLY MELANOMA SKIN CANCER DETECTION BY PROCESSING DERMOSCOPIC IMAGES USING TRADITIONAL DEEP-LEARNING MODELS

BY

S.M. MARUF HOSSAIN
ID: 201-15-3470
AND

JUNAYED AREFIN
ID: 201-15-3294

FINAL YEAR DESIGN PROJECT REPORT

This Report Presented in Partial Fulfillment of the Requirements for the Degree of Bachelor of Science in Computer Science and Engineering

Supervised By

MOHAMMAD JAHANGIR ALAM
Lecturer (Senior Scale)
Department of Computer Science and Engineering
Daffodil International University

Co-Supervised By

MD. ASSADUZZAMAN
Lecturer (Senior Scale)
Department of Computer Science and Engineering
Daffodil International University

DAFFODIL INTERNATIONAL UNIVERSITY

DHAKA, BANGLADESH

July 2024

APPROVAL

This Project titled "**Early Melanoma Skin Cancer Detection by Processing Dermoscopic Images Using Traditional Deep Learning Models,"** submitted by **S.M. MARUF HOSSAIN** and **JUNAYED AREFIN** to the Department of Computer Science and Engineering, Daffodil International University, has been accepted as satisfactory for the partial fulfillment of the requirements for the degree of B.Sc. in Computer Science and Engineering and approved as to its style and contents. The presentation has been held on **14 July, 2024**.

BOARD OF EXAMINERS

____

Dr. Md. Ismail Jabiullah **Board Chairman**
Professor
Department of CSE
Faculty of Science & Information Technology
Daffodil International University

____

Mr. Saiful Islam **Internal Examiner 1**
Assistant Professor
Department of CSE
Faculty of Science & Information Technology
Daffodil International University

____

Mr. Afjal Hossan Sarower **Internal Examiner 2**
Lecturer (Senior Scale)
Department of CSE
Faculty of Science & Information Technology
Daffodil International University

____

Dr. Ahmed Wasif Reza **External Examiner**
Professor
Department of Computer Science &
Engineering
East West University

DECLARATION

We hereby declare that this project has been done by us under the supervision of **Mohammad Jahangir Alam, Lecturer (Senior Scale), Department of Computer Science and Engineering, Daffodil International University.** We also declare that neither this project nor any part of this project has been submitted elsewhere for the award of any degree or diploma.

Supervised by:

MOHAMMAD JAHANGIR ALAM
Lecturer (Senior Scale)
Department of CSE
Daffodil International University

Co-Supervised by:

MD. ASSADUZZAMAN
Lecturer (Senior Scale)
Department of CSE
Daffodil International University

Submitted by:

Maruf

S.M. MARUF HOSSAIN
ID: 201-15-3470
Department of CSE
Daffodil International University

Junayed

JUNAYED AREFIN
ID: 201-15-3294
Department of CSE
Daffodil International University

ACKNOWLEDGEMENT

First, we express our heartiest thanks and gratefulness to almighty for His divine blessing making it possible for us to complete the final year project/internship successfully.

We are grateful and wish our profound indebtedness to **Mohammad Jahangir Alam**, **Lecturer (Senior Scale)**, Department of CSE Daffodil International University, Dhaka. Deep Knowledge & keen interest of our supervisor in the field of "*Deep Learning*" to carry out this project. His endless patience, scholarly guidance, continual encouragement, constant and energetic supervision, constructive criticism, valuable advice, reading many inferior drafts, and correcting them at all stages have made it possible to complete this project.

We would like to express our heartiest gratitude to the **Head of the Department of CSE**, for his kind help in finishing our project and also to other faculty members and the staff of the Department of CSE, Daffodil International University.

We would like to thank our entire course mate in Daffodil International University, who took part in this discussion while completing the course work.

Finally, we must acknowledge with due respect the constant support and patience of our parents.

ABSTRACT

Skin cancer is one of the most dangerous health issues in the world. A huge number of people are affected every year. There are three types of skin cancer, and the most common one is melanoma, which is also the most dangerous skin cancer with a higher chance of metastasis and death. Roughly 1-2% of cases of skin cancer are caused by melanoma and affect 3-5% of the population. Current diagnostic methods are time-consuming and prone to human error, which requires more precise and effective detection methods. The goal of this project is to build a deep learning model architecture that can identify melanoma with high accuracy and low time consumption, utilizing the ISIC 2019-2020 Melanoma dataset. Our model aims to improve the accuracy of advanced image processing with deep learning techniques, which could facilitate early intervention and potentially life-saving treatments. The ISIC 2019-2020 datasets provide a huge quantity of dermoscopic images, which can serve as an excellent foundation for training and validating our deep-learning models. We use some recent famous and well-performed convolutional neural networks (CNNs) models and train the models, such as ResNet50, ConvNeXt, EfficientNetV2, VGG16, MobileNetV3, and Swin Transformer, to extract features indicative of melanoma skin cancer images and predict results accurately based on all these model's prediction accuracy. We also created a web-based application to do the cancer prediction by comparing the results of all these 6th models to get an accurate result. This study shows the essential role of technology: to keep coming up with new ideas for advancing medical diagnostics to fight against the deadliest melanoma skin cancer. We tried to build up a deep-learning model that can detect exact skin cancer cells with high accuracy and low time consumption based on the ISIC 2019-2020 melanoma dataset.

TABLE OF CONTENTS

Contents	Page No

LIST OF FIGURES

LIST OF TABLES

LIST OF ACRONYMS

CNN	Convolutional Neural Network

CHAPTER 1
INTRODUCTION

1.1 Overview:

Melanoma is the most lethal type of skin cancer. It has a higher likelihood of spreading to other parts of the body compared to other skin cancers and can be more deadly if not detected and treated early. This cancer changes the skin color due to the abnormal growth of pigment-producing cells. Initially, the cancerous cells are confined to the epidermis, the top layer of the skin, and have not yet invaded deeper layers to spread elsewhere in the body. Melanoma begins in melanocytes, which are the skin cells that produce melanin, the pigment responsible for skin and hair color. It often likely treatable in the early stages of the cancer, but the challenging part occurs when we need to differentiate or identify between melanoma and other non-cancerous skin tumors or infections in the early stages. But if it is left undetected and untreated, it can progress to a more advanced stage, invade deeper layers of the skin, and potentially spread to other parts of the body through the lymphatic system and bloodstream, significantly increasing the risk of complications and mortality. To achieve better classification results for predicting and categorizing melanoma cancer into malignant and benign lesions using dermatology images, a complex classification model is necessary. Researchers have identified three main phases for detecting melanoma-affected cells: (1) identifying the skin boundary, (2) extracting features, and (3) classification. Many studies have been done to find solutions to cure melanoma in its early stages and have also found tremendous success using many well-known machine learning algorithms, including Artificial Neural Network (ANN), CNN, Support Vector Method (SVM), Heuristic Algorithm, Multi-class Classification, DSCC, and the Chaotic World Cup Optimization algorithm (CWCOA). Although they achieved a high accuracy rate, the processes are time-consuming and have some limitations, like struggles with different skin tones (all research is done using the skin images of white people) and protecting the privacy of the patients. However, a biopsy provides a better diagnosis that is only possible based on surgery, but it is a painful experience for the patients, which causes an unpleasant experience for them. The main purpose of this paper is to train different well-known deep learning models that have higher accuracy in image processing and classification and compare all those deep learning models to predict the cancer image accurately and overcome these drawbacks, We also want to compare our predicted results with dermatologist assessments to determine the efficiency of our system.

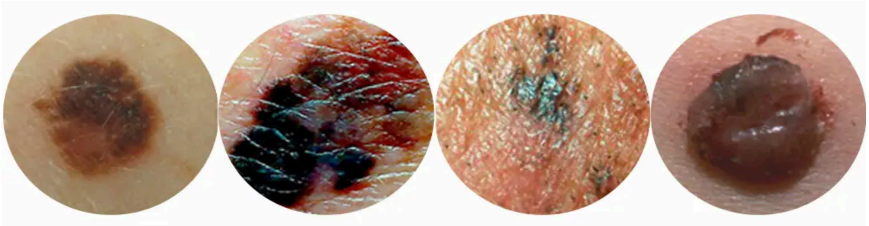

Figure 1.1.1: Some dermoscopic examples of Melanoma

1.2 Background and Present State

Background State:

Skin cancer is one of the most dangerous health issues in the world. A huge number of people are affected every year. They are categorized into three types: basal cell carcinoma, squamous cell carcinoma, and melanoma. Among these, the most common one is melanoma, which is also the most dangerous skin cancer with a higher chance of metastasis and death. Roughly 1-2% of cases of skin cancer are caused by melanoma and affect 3-5% of the population. Effective treatment and higher survival rates for melanoma depend on early identification, the best diagnosis, and treatment. Current diagnostic methods are time-consuming and prone to human error, which requires more precise and effective detection methods. Technological developments in deep learning and artificial intelligence (AI) have demonstrated great promise for revolutionizing medical diagnostics, especially in the area of skin cancer detection.

Present State:

Detecting skin cancer in its current state requires a combination of visual inspection, dermoscopic imaging, and histological analysis. In the present time, dermatologists mostly rely on their clinical skills to identify suspicious lesions, and this process is inherently subjective by nature. But dermoscopy is still a skill and labor-intensive operation. It also enhances diagnostic accuracy and is a time-consuming process. This project aims to advance the field of melanoma detection by developing a deep learning model architecture that can identify melanoma with high accuracy and low time consumption, utilizing the ISIC 2019-2020 melanoma dataset. The ISIC 2019-2020 datasets provide a huge quantity of dermoscopic images, which can serve as an excellent foundation for training and validating our deep-learning models. In our project, we train different highly efficient deep learning models and compare the results of those models to get an accurate result in decision-making for cancer images. These models can also predict the result quickly, which is beneficial for saving time.

1.3 Problem Statement

To stop the pigmented cells and spread of melanoma cancer across the skin, which makes the cancer deadliest, and to cure this cancer permanently without any unpleasant experience, early cancer cell detection is the most effective and needed way to get relief from this most dangerous skin cancer. However, the testing process is time-consuming and requires a high-configuration device with high processing power and high internet bandwidth. Patient privacy and skin tone are also issues here, as the hospitals are concerned about private data and the model struggles with different skin tones. Also, the class imbalance has a bad impact on the accuracy. So our target is to build a comparable deep learning model that can overcome these drawbacks in a less time-consuming and cost-effective way.

1.4 Objectives

Our objective is to create a computer-aided system for early and reliable melanoma detection by developing more accurate and reliable models using deep-learning methods. We train highly efficient convolutional neural network (CNN) models to predict skin cancer and provide an efficient prediction over skin cancer images by using the results of all our trained models together so that they can be more accurate. We are using newly developed models that are in good demand and more efficient than other traditional models so that they can predict in a quick time. So the models we used are less time-consuming which enhances performance and user satisfaction. Based on our plan, we also created a web application that a user can use to predict skin cancer images and know whether the image contains cancerous cells or not. By addressing limitations and fostering trust, we aim to encourage the wider adoption of AI tools in melanoma detection.

1.5 Scope and Limitations

Scope:

With the Deep Learning model, we are trying to build a well-performed, less time-consuming, and effective computer aid method that can work with diverse data and reduce communication costs and bandwidth requirements. The number of papers on using deep learning models and comparing the results to get more accurate results in the skin cancer detection field is relatively small, especially on melanoma skin cancer. Also, we will conduct a detailed comparison between the model's performance and dermatologists' assessments for a non-invasive, efficient solution for skin cancer, and although they are not replacements for biopsies, an accurate AI model can potentially reduce unnecessary biopsies. Highly effective solutions for early skin cancer detection and treatment can be achieved by using highly efficient deep learning models and their results together, which will increase the trust of patients and healthcare providers in AI tools and also lead to wider adoption.

Limitations:

We are using the ISIC 2019-2020 melanoma skin cancer image dataset in our paper to train our model and do the prediction. ISIC is an open-source platform that gathers and stores skin cancer images from different sources, providing high-quality data to advance the detection and diagnosis of skin cancer through AI and other computational methods, but we weren't able to collect melanoma skin cancer data by ourselves from our regions, which is one of the biggest limitations for us here in this research. Collecting data from the local community gives us knowledge about the people of the country, which gives us a great opportunity to work for the local people and provide them with a good solution for their skin cancer illness. That would also be a great milestone in our motivation for this research paper. We are using our dataset to train CNN models to predict the result, but CNNs can easily overfit the training data, especially when the dataset is small or not diverse enough. This leads to poor generalization of unseen data. CNNs generally need substantial amounts of labeled data to perform well. This can be a significant limitation in domains where labeled data is scarce or expensive to obtain. If the dataset is imbalanced (significantly more benign lesions than malignant ones), the model may become biased toward the more frequent classes.

1.6 Report Organization

Chapter 1 describes the main idea of why we are concerned about 'Early Melanoma Skin Cancer Detection By Processing Dermoscopic Images Using Traditional Deep-Learning Models'. Our Background and Present State, Problem Statement, Objectives, Scope, and Limitations.

In Chapter 2, we discuss the Summary, Limitations, and Outcome of the previous related research on Melanoma skin cancer.

Chapter 3 points out our Research Methodology.

1.7 Summary

Melanoma is the most dangerous form of skin cancer, characterized by the abnormal growth of melanocytes, the pigment-producing cells in the skin. Early detection is crucial, as it is treatable in the initial stages but challenging to distinguish from non-cancerous lesions. If undetected, melanoma can invade deeper skin layers and metastasize, increasing the risk of complications and mortality. Current diagnostic methods are time-consuming and prone to human error, necessitating more precise and efficient detection methods. This project aims to train and compare various deep-learning models to predict melanoma with high accuracy, efficiency, and less time consumption. This project seeks to develop a reliable, cost-effective system for early melanoma detection, encouraging wider adoption of AI tools in clinical settings. A web application is also created for users to predict cancerous cells, enhancing performance and user satisfaction.

CHAPTER 2
LITERATURE REVIEW

2.1 Overview

To achieve the goal of computer-aid-based melanoma cancer detection, many researchers left their footprint in this sector of finding the best possible way of detecting melanoma skin cancer cells in the early stages of cancer and used different popular machine learning classification methods like Artificial Neural Network (ANN), Convolutional Neural Networks (CNN), Support Vector Method (SVM), Heuristic algorithms, Multi-class Classification, DSCC, Chaotic World Cup Optimization algorithm (CWCOA) and also achieved a brilliant accuracy. But these algorithms also have their drawbacks, like some models require a large amount of labeled data, are computationally demanding and also have complex network structures, and time-consuming performance. Most of the researchers used the data HAMM10000 or The International Skin Imaging Collaboration (ISIC) database to do their research. They got classification accuracy between 80%-95%. However, they also encountered challenges with using diverse databases, as the process was time-consuming. Additionally, their research primarily focused on fair-skinned individuals, excluding dark-skinned individuals. This was due to the publicly available datasets used in the study containing mostly skin cancer images of fair-toned skin.

2.2 Related Works

Jinen Daghrir (2020) proposes KNN, SVM, and CNN models for skin cancer classification, achieving a testing accuracy , 57.3%, 71.8%, and 85.5%. They made use of a collection of features that defined the borders, color. and texture of a skin lesion. Then, to enhance their effectiveness, these techniques are integrated.

Md. Arman Hossin (2020) proposes CNN, Resnet50 models for skin cancer classification, achieving a testing accuracy of 93.58%, 83%. In this research, a multi-layered CNN strategy with several regularization approaches called dropout and batch normalization is used to classify dermoscopic pictures in order to predict skin cancer.

Khalid M. Hosny (2018) proposes DCNN, SVM, and ANN models for skin cancer classification, achieving a testing accuracy of 98.61%, 96%, and 92.5%. This research proposes an automated method for the classification of skin lesions. This approach makes use of transfer learning and a pre-trained deep learning network.

Yuexiang Li (2018) proposes FCN-8s, U-net, LIN, and J. Kawahara, LFN models for skin cancer classification, achieving a testing accuracy of 93.3%, 92.0%, 95.0%, 98.5%, and 90.2%. To deal with all three main goals caused in the field of skin lesion image processing, lesion segmentation, lesion dermoscopic feature extraction, and lesion classification, they present two deep learning algorithms in this study.

Ni Zhang (2020) proposes CNN models for skin cancer classification, achieving a testing accuracy of 97%. This research proposes an innovative image processing based technique for skin cancer early detection.

Noortaz Rezaoana (2020) implemented the proposed model, VGG-16, VGG-19 models for skin cancer classification, achieving testing accuracy of 79.45%, 69.57%, and 71.19%. The research proposes an automated method for the classification of skin cancer. In this study, nine different forms of skin cancer have been classified.

Mahamudul Hasan (2019) implemented proposed model for skin cancer classification, achieving a testing accuracy of 89.5%. This research proposes a machine learning and image processing-based artificial skin cancer detection system.

Mario Fernando Jojoa Acosta (2021) implemented eVida M6 model for skin cancer classification, achieving a testing accuracy of 90.4%. This study has access to an automated, reliable method that can use a skin pigmentation tool or a dermatoscopic image of lesions to identify melanoma.

Vidya M. (2020) implemented SVM, KNN models for skin cancer classification, achieving a testing accuracy of 97.8%, 85 %. This study uses methodologies for lesion detection for performance criteria, accuracy, and efficiency to perform automatic skin lesion detection.

Table 2.2.1: Related Works analysis with previous work

Title	Author	Models	Accuracy
Melanoma skin cancer detection using deep learning and classical machine learning techniques: A hybrid approach	Jinen Daghrir	KNN, SVM, CNN	57.3%, 71.8%, 85.5%,
Melanoma Skin Cancer Detection Using deep learning and advanced regularizer.	Md. Arman Hossin	CNN, Resnet50	93.58%, 83%
Skin Cancer Classification using Deep Learning and Transfer Learning	Khalid M. Hosny	DCNN, SVM,	98.61%, 96%, 92.5%

		ANN	
Skin Lesion Analysis towards Melanoma Detection Using Deep Learning Network	Yuexiang Li	FCN-8s, U-net, LIN, J. Kawahara, LFN	93.3%, 92.0%, 95.0%, 98.5%, 90.2%.
Skin Cancer Diagnosis Based on Optimized Convolutional Neural Network	Ni Zhang	CNNs	97%
Detection and Classification of Skin Cancer by Using a Parallel CNN Model	Noortaz Rezaoana	proposed model, VGG-16, VGG-19	79.45%, 69.57%, 71.19%
Skin Cancer Detection Using Convolutional Neural Network	Mahamudul Hasan	proposed model	89.5%
Melanoma diagnosis using deep learning techniques on dermatoscopic images	Mario Fernando Jojoa Acosta	eVida M6	90.4%
Skin Cancer Detection using Machine Learning Techniques	Vidya M	SVM, KNN	97.8%, 85 %
Melanoma Skin Cancer Detection Using Image Processing and Machine Learning Techniques	MA. Ahmed Thaajwer	proposed	83%

2.3 Comparison between existing works

The comparison of existing works on skin cancer is really important to understand the scope of the field and identify areas for further improvement. So, here we compare some studies based on their methodologies, models, and tested accuracies. From the first paper, jinen Daghrir (2020) used KNN: 57.3%, SVM: 71.8%, and CNN: 85.5% and their study highlights the comparative performance of traditional machine learning models and deep learning models CNN significantly outperformed KNN and SVM, the overall performance indicates improvement in utilizing more advanced deep learning models. In the Md. Arman Hossin (2020) paper, they used CNN: 93.58%, ResNet50: 83% and the main outcome was to use of regularization techniques contributed to improved performance of the CNN models. From Khalid M. Hosny (2018) paper, they used DCNN: 98.61%, SVM: 96%, and ANN: 92.5%, and there main aims are automated skin lesion classification with pre-trained networks and transfer learning. In the Yuexiang Li (2018) paper, they used FCN-8s: 93.3%, U-Net: 92.0%, LIN: 95.0%, LFN: 98.5%, and LFN (J. Kawahara): 90.2% and their main target is Lesion segmentation, dermoscopic feature extraction, and lesion classification. In Ni Zhang (2020) paper, they used CNN:97% and their main finding is that the innovative image processing methods employed contributed to the model's performance. From Noortaz Rezaoana (2020) is used Proposed model: 79.45%, VGG-16: 69.57%, and VGG-19: 71.19%, and their main finding is the challenges in classifying multiple types of skin cancer.

TABLE 2.3.1: COMPARISON ANALYSIS BETWEEN EXISTING WORKS

Author	Highest Accuracy	Key Strengths	Limitations
Jinen Daghrir (2020)	85.5% (CNN)	Utilization of diverse features	Lower accuracy with KNN, SVM
Md. Arman Hossin (2020)	93.58% (CNN)	Regularization techniques	Lower accuracy with ResNet50
Khalid M. Hosny (2018)	98.61% (DCNN)	Transfer learning, pre-trained networks	Complexity, resource-intensive
Yuexiang Li (2018)	98.5% (LFN)	Comprehensive image processing tasks	Complexity of models
Ni Zhang (2020)	97%	Early detection focus	Limited model diversity
Noortaz Rezaoana()	79.45% (Proposed)	Multi-type classification	Lower accuracies overall

2.4 Summary

From all those papers, the highest accuracy was achieved by Khalid M. Hosny (2018) with DCNN at 98.61%, with deep learning and transfer learning. Yuexiang Li's LFN model also performs exceptionally well at 98.5%. So, DCNN and LFN, with transfer learning, achieved higher accuracy. The combination of traditional machine learning models with deep learning models shows varied results, indicating the potential limitations and benefits. And we got some scope and ideas to create something new with those Deep learning.

CHAPTER 3
METHODOLOGY

3.1 Overview

This chapter provides a detailed exploration of the proposed methodology, software requirements, project management strategies, and financial analysis for developing a deep learning-based system for early and accurate melanoma detection. The aim is to create a robust, efficient, and user-friendly diagnostic tool capable of accurately classifying skin lesions as malignant or benign using dermoscopic images. The methodology section will detail the approaches and techniques used to collect, preprocess, and analyze the data, as well as the design and implementation of various deep learning models. It will cover the process of training, validating, and testing these models using the ISIC 2019-2020 dataset. The software requirement analysis section will identify the functional and non-functional requirements necessary for the system's development, ensuring it meets the needs of end-users, including dermatologists and patients. This section will also address the challenges related to data imbalance, and privacy, and propose strategies to mitigate these issues. In the Project Management and Financial Analysis section, we discuss the costs of project development and management. Overall, this chapter provides a comprehensive framework for developing a high-performance, reliable, and user-centric melanoma detection system, leveraging the latest advancements in deep learning and artificial intelligence.

3.2 Proposed Methodology

We want to make a website or a mobile app after our proposed model works perfectly with high accuracy and is less time-consuming. Doctors or medical help providers can predict early cancer by uploading pictures of the suspicious cells, get a result as quickly as they desire, and start the treatment quickly if they think the cells are dangerous for the patient's body. This is the main concept of our project.

Data Collection: To ensure the success of a Deep Learning model for Melanoma skin cancer, a robust Data Collection/Input-Output Analysis is imperative. First, we collect data from ISIC. ISIC is the international society for dermoscopic images of skin disease and it also so much popular. It has an open source public access archive designed to help reducing melanoma mortality. Dataset has 11400 images and also ISIC contain different types of skin dermoscopic images.

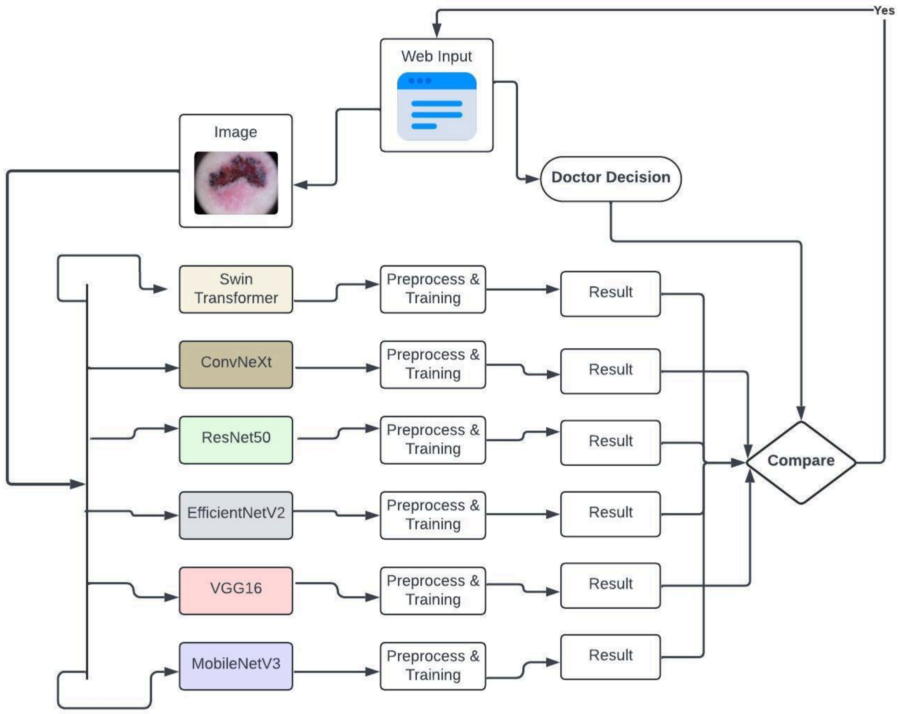

Figure 3.2.1: Design of our system and how it going to work.

3.3 Software Requirements

1. Deep learning framework (e.g., TensorFlow, PyTorch) to implement the chosen deep learning models.
2. Tools for data preprocessing, visualization, and model evaluation.
3. Secure communication protocols for data exchange between participating institutions and the central server (if applicable).

3.4 Project Management and Financial Analysis

Our goal is to create a website that compares different highly efficient Deep Learning models and generates an accurate result with the functionality so that dermatologists and patients can upload an image and get a skin cancer prediction related to melanoma. We first require a small amount of funding to develop a website, integrate it with the model, and store that information.

Table 3.4.1: Estimated Development Cost

SN	Components	Estimated Cost ($)
01.	**Development Costs:**	
	Website Development	120-150
02.	**Operational Costs (Annual):**	
	Hosting and Servers	55-60$
03.	**Miscellaneous Expenses:**	
	Domain Name and SSL Certificate	10$ + 5$
	Legal and Administrative	10$
Total Estimated Cost		200-235

3.5 Summary

This chapter outlines the methodology, requirement analysis, and design specifications for developing a deep learning-based system for early and accurate melanoma detection. The goal is to create a robust and efficient diagnostic tool using dermoscopic images. The financial analysis provides a budget overview, covering development, personnel, and operational costs. Overall, this chapter offers a comprehensive framework for developing a high-performance, reliable, and user-centric melanoma detection system.

CHAPTER 4
IMPLEMENTATION

4.1 Overview

We use the ISIC 2019-2020 dataset to train our models for making predictions. ISIC is an organization that collects data from different sources for skin cancer images. We use dermoscopic skin cancer images in our model for training and prediction. We used CNN-based models ResNet50, EfficiantNetV2, VGG16, MobileNetV3, ConvNeXt, and Swin Transformer and achieved good accuracy. We also created a web application where dermatologists and patients can upload cancer pictures and see the predictions. We made the prediction by comparing the results of all our trained models and also doing a comparison between the model's performance and dermatologist assessments, which will be given input directly to the website by the dermatologists to generate a more accurate result and monitor the model's efficiency.

4.2 Train Model

In this paper, we used a total of 6 highly efficient CNN models ResNet50, EfficiantNetV2, VGG16, MobileNetV3, ConvNeXt, and Swin Transformer, and achieved good performance and accuracy.

ResNet50:

ResNet50 is a powerful deep convolutional neural network renowned for its performance in image classification tasks. It utilizes residual blocks with identity shortcuts, which help train very deep networks by addressing the vanishing gradient issue. This architecture comprises convolutional layers, batch normalization, ReLU activations, pooling layers, and fully connected layers.

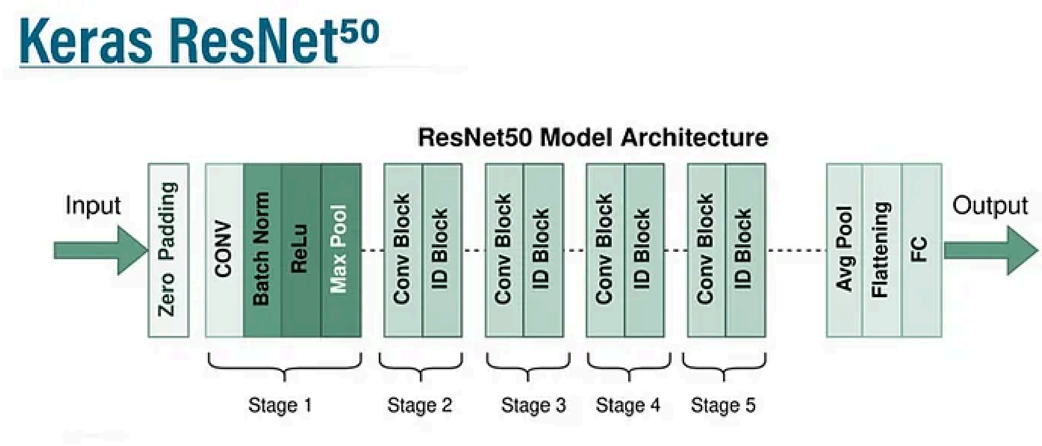

Figure 4.2.1: ResNet-50 architecture

Using ResNet50 in our project, we achieved a great result with 95% accuracy. Here is how we use this model to make predictions.

Data Preparation: The dataset of dermoscopic images, categorized into benign and malignant classes, was loaded from Google Drive. The images and labels were stored in a Pandas DataFrame and shuffled for randomness.

Data Visualization and Splitting: Class distributions were visualized, and sample images were displayed. The dataset was split into training and testing sets (75-25 split).

Data Augmentation: ImageDataGenerator was used for data augmentation on the training set to enhance generalization, while the validation and test sets were only preprocessed.

Model Design and Transfer Learning: A pre-trained ResNet50 model, with frozen layers, was used as the base model. Two new dense layers with ReLU activation and an output layer with Softmax activation were added for binary classification.

Model Compilation and Training: The model was compiled using the Adam optimizer and categorical cross-entropy loss function. Early stopping was implemented to avoid overfitting. Training was conducted on augmented training data, with validation performed on the test set.

Model Evaluation: The trained model's performance was evaluated on the test set, and metrics like accuracy, precision, recall, and F1-score were calculated. Predictions were visualized with true and predicted labels.

EfficiantNetV2:

EfficientNetV2B0 is a state-of-the-art convolutional neural network known for its efficiency and accuracy in image classification tasks. It scales up the network width, depth, and resolution systematically to achieve better performance with fewer computational resources. The architecture includes convolutional layers, batch normalization, ReLU activations, pooling layers, and fully connected layers.

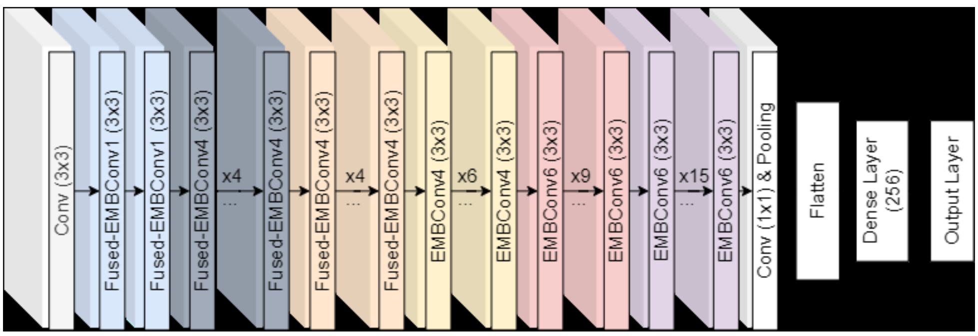

Figure 4.2.2: EfficiantNetV2 architecture

EfficientNets are among the most powerful convolutional neural network (CNN) models available today. Despite the emergence of Vision Transformers, which have surpassed EfficientNets in accuracy, EfficientNetV2 demonstrates that CNNs are still highly relevant. It not only enhances accuracy but also decreases training time and latency. We train this model with our dermoscopic melanoma skin cancer images and achieve a great result with 92.73% accuracy. This is how we trained our EfficiantNetV2 model,

Data Preparation: The dataset of dermoscopic images, categorized into benign and malignant classes, was loaded from Google Drive. The images and labels were stored in a pandas DataFrame and shuffled for randomness.

Data Visualization and Splitting: Class distributions were visualized, and sample images were displayed. The dataset was split into training and testing sets (75-25 split).

Data Augmentation: ImageDataGenerator was used for data augmentation on the training set to enhance generalization, while the validation and test sets were only preprocessed.

Model Design and Transfer Learning: A pre-trained EfficientNetV2B0 model, with frozen layers, was used as the base model. Two new dense layers with ReLU activation and an output layer with Softmax activation were added for binary classification.

Model Compilation and Training: The model was compiled using the Adam optimizer and categorical cross-entropy loss. Early stopping was employed to avoid overfitting. The model was trained on augmented training data and validated on the test set.

Model Evaluation: The trained model's performance was evaluated on the test set, and metrics like accuracy, precision, recall, and F1-score were calculated. Predictions were visualized with true and predicted labels.

VGG16:

VGG16 is a convolutional neural network architecture recognized for its simplicity and effectiveness in image classification tasks. It includes convolutional layers, pooling layers, and fully connected layers with a large number of parameters, making it a powerful model for feature extraction.

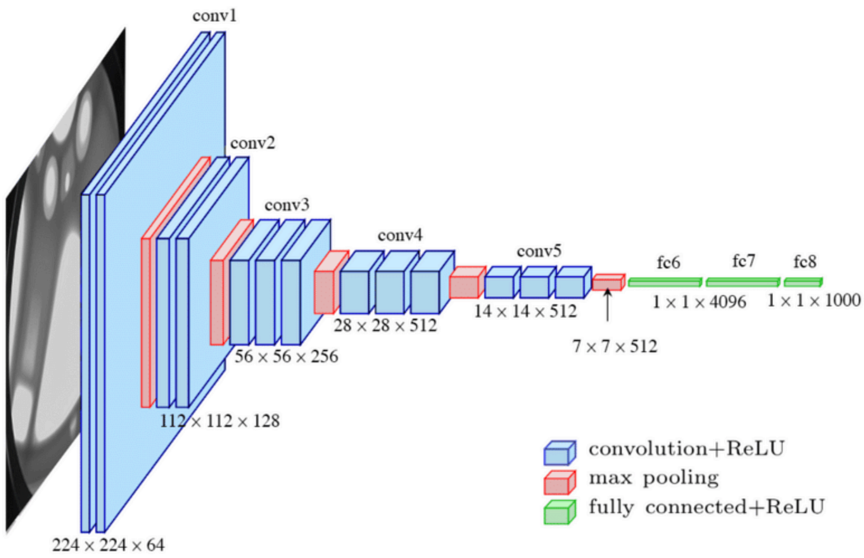

Figure 4.2.3: Vgg16 architecture

Data Preparation: The dataset of dermoscopic images, categorized into benign and malignant classes, was loaded from Google Drive. The images and labels were stored in a pandas DataFrame and shuffled for randomness.

Data Visualization and Splitting: Class distributions were visualized, and sample images were displayed. The dataset was split into training and testing sets (75-25 split).

Data Augmentation: ImageDataGenerator was used for data augmentation on the training set to enhance generalization, while the validation and test sets were only preprocessed.

Model Design and Transfer Learning: A pre-trained VGG16 model, with frozen layers, was used as the base model. Dense layers with ReLU activation, batch normalization, and dropout layers were added for regularization, and an output layer with Softmax activation was used for binary classification.

Model Compilation and Training: The model was compiled with the Adam optimizer and categorical cross-entropy loss. Early stopping, model checkpointing, and learning rate reduction on plateau were used to enhance training. The model was trained on the augmented training data and validated on the test set.

Model Evaluation: The trained model's performance was evaluated on the test set, and metrics like accuracy, precision, recall, and F1-score were calculated. Predictions were visualized with true and predicted labels.

MobileNetV3:

MobileNetV3 is a state-of-the-art neural network architecture optimized for mobile and embedded devices, balancing performance and efficiency. It utilizes depthwise separable convolutions to significantly reduce computation and model size. The architecture includes inverted residual blocks with linear bottlenecks to maintain a streamlined model structure, expanding and compressing feature dimensions efficiently. Additionally, MobileNetV3 incorporates Squeeze-and-Excitation (SE) modules to enhance feature recalibration by modeling channel interdependencies. The use of the Hard-Swish activation function further improves efficiency. MobileNetV3 was optimized using Network Architecture Search (NAS) to find the best architecture within specified constraints, resulting in two variants: MobileNetV3-Large for higher accuracy and MobileNetV3-Small for faster inference and lower computational cost.

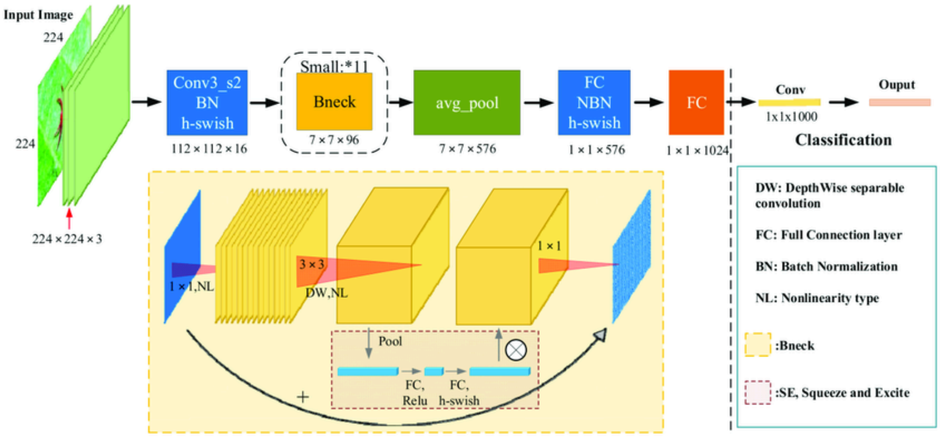

Figure 4.2.4: MobileNetV3 architecture

We got significant accuracy using this model in our cancer protection.

Data Preparation: The dataset of dermoscopic images, categorized into benign and malignant classes, was loaded from Google Drive. The images and labels were stored in a Pandas DataFrame and shuffled for randomness.

Data Visualization and Splitting: Class distributions were visualized, and sample images were displayed. The dataset was split into training and testing sets (75-25 split).

Data Augmentation: ImageDataGenerator was used for data augmentation on the training set to enhance generalization, while the validation and test sets were only preprocessed.

Model Design and Transfer Learning: A pre-trained MobileNetV3Large model, with frozen layers, was used as the base model. Dense layers with ReLU activation and Dropout layers were added for regularization, and an output layer with Softmax activation was used for binary classification.

Model Compilation and Training: The model was compiled with the Adam optimizer and categorical cross-entropy loss. Early stopping was used to enhance training. The model was trained on the augmented training data and validated on the test set.

Model Evaluation: The trained model's performance was evaluated on the test set, and metrics like accuracy, precision, recall, and F1-score were calculated. Predictions were visualized with true and predicted labels.

ConvNeXt:

ConvNeXtTiny is a modern convolutional neural network architecture designed to handle image classification tasks efficiently. It utilizes advanced techniques for improved accuracy and performance while maintaining computational efficiency. The architecture includes convolutional layers, batch normalization, ReLU activations, pooling layers, and fully connected layers.

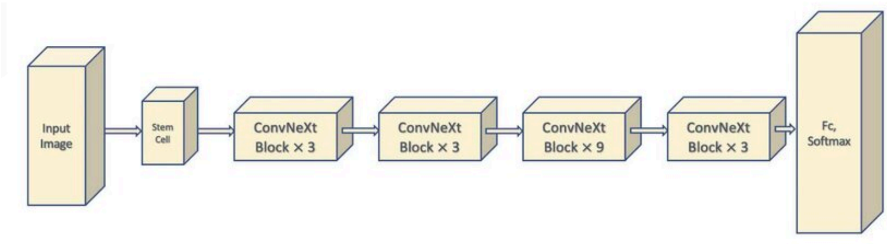

Figure 4.2.5: ConvNeXt architecture

From all of the models we used, ConvNeXt achieved the highest performance and accuracy for our cancer images. We evaluate the model like this.

Data Preparation: The dataset of dermoscopic images, categorized into benign and malignant classes, was loaded from Google Drive. The images and labels were stored in a Pandas DataFrame and shuffled for randomness.

Data Visualization and Splitting: Class distributions were visualized, and sample images were displayed. The dataset was split into training and testing sets (75-25 split).

Data Augmentation: ImageDataGenerator was used for data augmentation on the training set to enhance generalization, while the validation and test sets were only preprocessed.

Model Design and Transfer Learning: A pre-trained ConvNeXtTiny model, with frozen layers, was used as the base model. Two new dense layers with ReLU activation and an output layer with Softmax activation were added for binary classification.

Model Compilation and Training: The model was compiled with the Adam optimizer and categorical cross-entropy loss. Early stopping was used to prevent overfitting. The model was trained on the augmented training data and validated on the test set.
Model Evaluation: The trained model's performance was evaluated on the test set, and metrics like accuracy, precision, recall, and F1-score were calculated. Predictions were visualized with true and predicted labels.

Custom Layer: A custom LayerScale layer was defined and incorporated into the model to adjust the scale of the inputs dynamically during training. This layer plays a crucial role in enhancing the model's flexibility and adaptability.

Swin Transformer:

The Swin Transformer (Shifted Window Transformer) is a hierarchical vision transformer model, designed for various computer vision tasks. It applies self-attention within local windows and shifts these windows across layers to capture global context efficiently. The hierarchical structure allows it to model different scales of visual information, making it suitable for tasks like image classification, object detection, and segmentation.

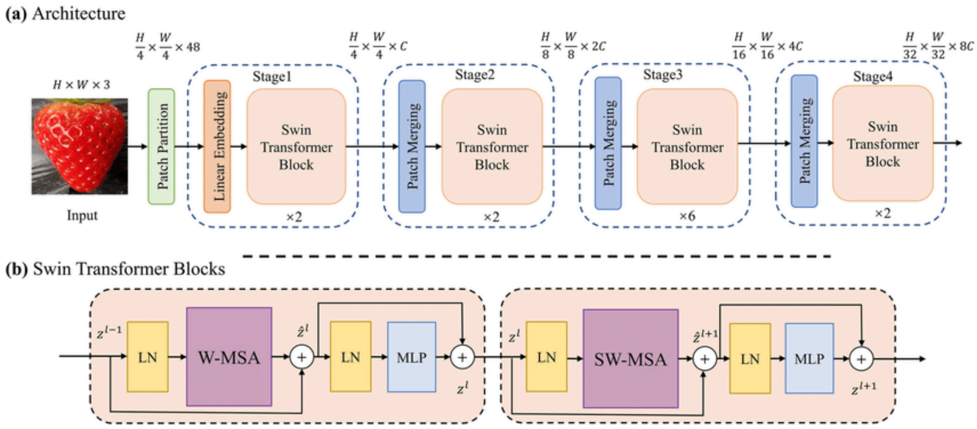

Figure 4.2.6: Swin Transformer architecture

We also achieved good accuracy from this model to train our melanoma skin cancer images. The way we did,
Data Preparation: The dataset was split into training and test sets. A custom SkinDataset class was created to handle data loading using PyTorch's Dataset and DataLoader classes. Image transformations included resizing and tensor conversion.
Model Initialization: The Swin Transformer model (swin-tiny-patch4-window7-224) was loaded with pre-trained weights. The output layer was adjusted to match the number of classes in the dataset.

Training: The model was trained using the training dataset, with the CrossEntropyLoss function, Adam optimizer, and a learning rate scheduler to optimize the learning process. The training was performed on a GPU.
Evaluation: After training, the model's performance was evaluated on the test dataset. Accuracy and classification reports were generated, and a subset of predictions was visualized to inspect model predictions visually.
Saving and Loading the Model: The trained model was saved to disk, and the process of loading the model and making predictions on new images was demonstrated.

4.3 Model Evaluation

We used a total of 6 CNN models, ResNet50, EfficiantNetV2, VGG16, MobileNetV3, ConvNeXt, and Swin Transformer. They all performed well with significant accuracy. But among all these 6 models, ConvNeXt and Swin Transformer performed best with 97.45% accuracy and 96.36% accuracy, respectively. The accuracy of other models is ResNet50 with 94.91% accuracy, EfficientNetV2 with 95.64% accuracy, VGG16 with 90.02% accuracy, and MobileNetV3 with 94.91% accuracy. So the accuracy is between 90% and 98%. The ConvNeXt and Swin Transformer models performed exceptionally well. The reasons for their strong performance can be attributed to several factors related to their architecture and design principles.

Table 4.3.1: Model Accuracy Table

Model Name	Accuracy
ConvNeXt	97.45%
Swin Transformer	96.36%
EfficientNetV2	95.64%
ResNet50	94.91%
MobileNetV3	94.91%
VGG16	90.02%

ConvNeXt:

1. **Modernized Convolutional Architecture**: ConvNeXt is inspired by the traditional convolutional neural networks (CNNs) but incorporates modern architectural improvements. It borrows ideas from both CNNs and transformers to optimize performance.
2. **Improved Design Choices**: ConvNeXt incorporates various design enhancements, such as large kernel sizes, fewer activation functions, and normalization layers, making it more efficient and powerful.
3. **Effective Use of Depthwise Convolutions**: Similar to MobileNetV3, ConvNeXt leverages depthwise separable convolutions, which reduce computational complexity while maintaining high performance.
4. **Hierarchical Feature Extraction**: ConvNeXt effectively captures hierarchical features through multiple layers, allowing it to understand and process complex patterns within images.

Swin Transformer:

1. **Hierarchical Transformer Architecture**: The Swin Transformer uses a hierarchical architecture that processes images at multiple scales, capturing both local and global features effectively.
2. **Shifted Window Approach**: Swin employs a shifted window mechanism for self-attention, which reduces computational overhead while maintaining the ability to model long-range dependencies.
3. **Efficient Self-Attention Mechanism**: By applying self-attention within local windows, Swin Transformer achieves a good balance between efficiency and performance, making it suitable for high-resolution image tasks.
4. **Generalization Capability**: The attention mechanism in transformers provides a robust way to generalize from the training data, which helps in achieving high accuracy on unseen test data.

Shared Factors

1. **Data Augmentation**: Both models benefited from extensive data augmentation during training, which helped in preventing overfitting and improving generalization.
2. **Transfer Learning**: Utilizing pre-trained weights from large datasets like ImageNet provided a strong foundation for both models, allowing them to leverage learned features and patterns.

3. **Advanced Optimization Techniques**: Both models were trained with advanced optimization techniques, including learning rate schedulers and effective loss functions, contributing to their high performance.
4. **Robust Evaluation**: Comprehensive evaluation using appropriate metrics ensured that the models were thoroughly tested, leading to reliable accuracy measurements.

4.4 Summary

The things we discuss here are the models we used in our paper and how we used the model to do the prediction with higher efficiency, and discuss the architecture of our used models. In model evaluation, we discuss the accuracy of our models and the reasons for producing a higher accuracy. It provides a clear idea about our model train and the reasons we selected these ResNet50, EfficiantNetV2, VGG16, MobileNetV3, ConvNeXt, and Swin Transformer 6 models to do the prediction and use in our paper. Overall, ConvNeXt and Swin Transformer are the best performance models, with accuracy of 97.45% and 96.36%.

CHAPTER 5
RESULT AND ANALYSIS

5.1 Overview

In this chapter, we present a detailed analysis of the results obtained from our experiments on skin cancer detection using various machine learning models. The objective is to evaluate the performance of different deep-learning architectures in accurately classifying skin lesions. We begin by outlining the experimental setup, including the dataset preparation, model training procedures, and the evaluation metrics used to assess the performance. We then provide a comprehensive comparison of the models, highlighting the accuracy and other key performance metrics achieved by each. Visualizations such as training and validation accuracy plots, confusion matrices, and sample predictions are included to support our analysis. Our experiments demonstrate that the ConvNeXt and Swin Transformer models achieved the highest accuracy, with ConvNeXt attaining 97.45% and Swin Transformer achieving 96.36%. We analyze the reasons behind the superior performance of these models, considering factors such as model architecture and training strategies. Additionally, we discuss any observed errors and potential areas for improvement in future research.

5.2 Experimental

This section details the experimental setup and methodology used to evaluate the performance of the different deep-learning models we used for melanoma skin cancer detection. The experiments were conducted using a well-curated dataset of melanoma skin lesion images, which was divided into training, validation, and test sets to ensure a comprehensive evaluation. The things we have done to train our models are,

Dataset Preparation: The dataset comprised high-resolution images of skin lesions, categorized into benign and malignant classes. Images were preprocessed to ensure uniformity in size and quality, with transformations such as resizing, normalization, and augmentation applied to enhance model robustness and generalization.

Model Training: We trained multiple state-of-the-art deep learning models, ResNet50, EfficiantNetV2, VGG16, MobileNetV3, ConvNeXt, and Swin Transformer, using the training dataset. Each model was fine-tuned with hyperparameter optimization, utilizing techniques like learning early stopping, and dropout to prevent overfitting. The training process was monitored using metrics such as training accuracy and loss, with validation sets used to tune model parameters.

Evaluation Metrics: To assess model performance, we employed a range of evaluation metrics, including accuracy, precision, recall, F1-score, and support. These metrics provided a comprehensive understanding of each model's ability to correctly classify skin lesions.

Hardware and Software: The experiments were conducted using a high-performance computing environment, leveraging GPUs to accelerate model training. The models were implemented using popular deep learning frameworks such as TensorFlow and PyTorch, ensuring the scalability and reproducibility of the experiments.

Analysis: Post-training, we evaluated the models on the test dataset to measure their generalization capabilities.

5.3 Performance

The performance measure depends on the test accuracy, test loss validation accuracy, and validation loss. If the difference between test accuracy and validation accuracy is too high, then the model is considered overfitting. Also, precision, recall, f1-score, and support of a model provide a brief description of the model and how well it is performing. Here we are showing how well our models are performing depending on all these factors.

ResNet50:

The accuracy and loss of our ResNet50 model after training the model with ISIC 2019-2020 melanoma skin cancer dermoscopic images are,

Accuracy: 94.91%

Loss: 0.24970

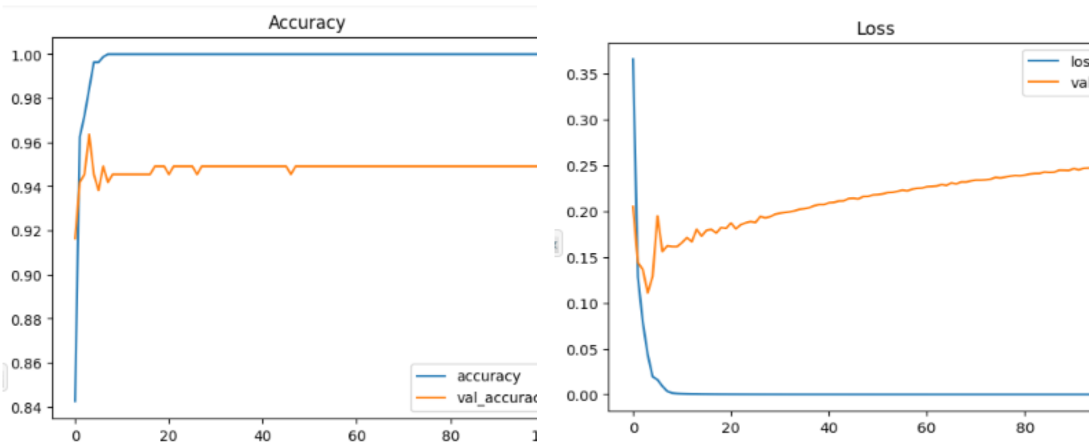

Figure 5.3.1: ResNet50 Accuracy & Loss chart

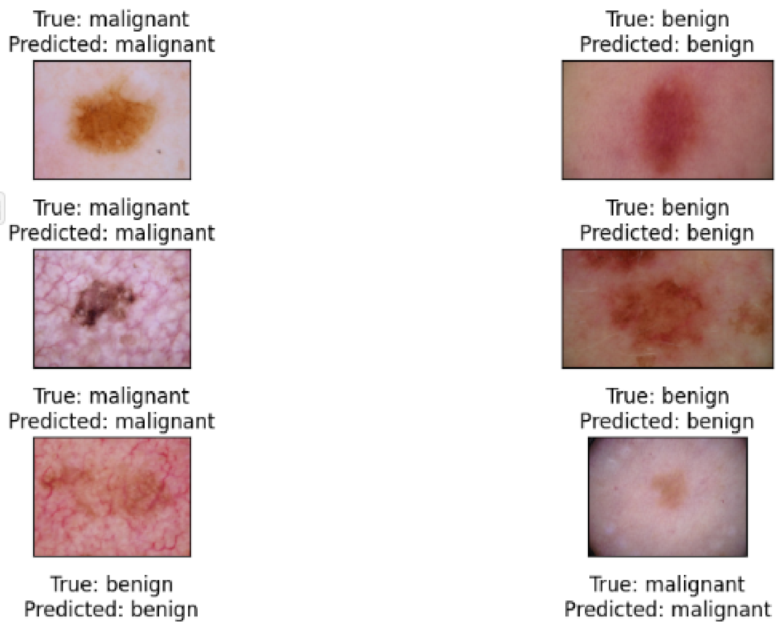

Figure 5.3.2: Some Random image predictions in ResNet50

	precision	recall	f1-score	support
benign	0.93	0.97	0.95	129
malignant	0.97	0.93	0.95	146
accuracy			0.95	275
macro avg	0.95	0.95	0.95	275
weighted avg	0.95	0.95	0.95	275

Figure 5.3.3: ResNet50 Model Performance

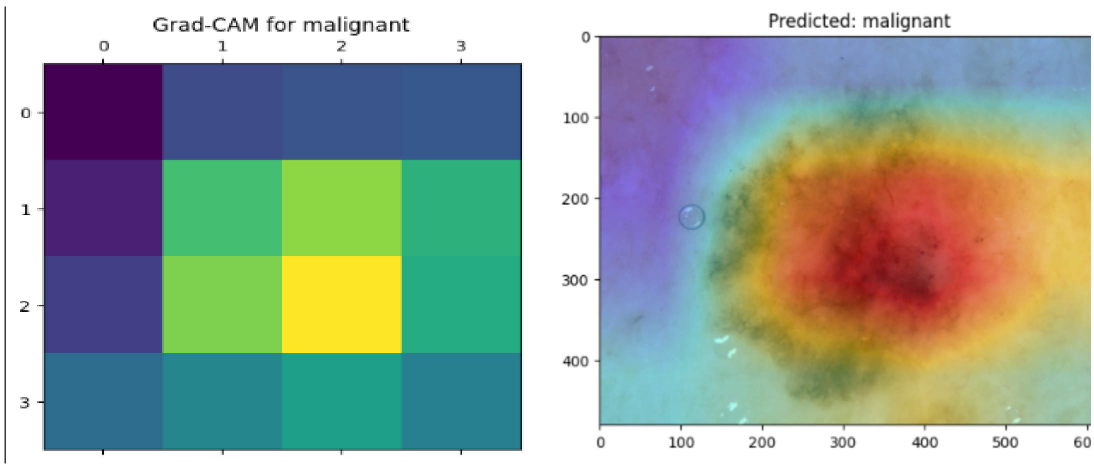

Figure 5.3.4: ResNet50 Grad-CAM heatmap

EfficientNetV2:

The accuracy and loss of our EfficientNetV2 model after training it with ISIC 2019-2020 melanoma skin cancer dermoscopic images are,

Accuracy: 95.64%

Loss: 0.27927

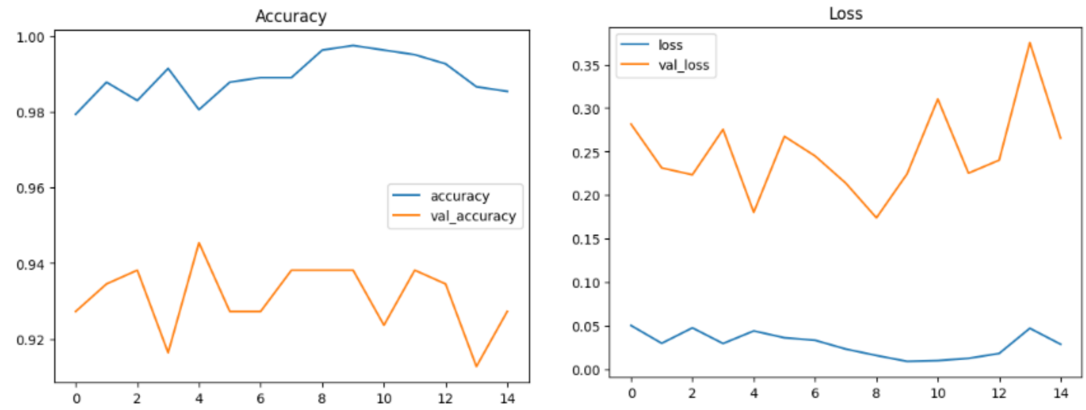

Figure 5.3.5: EfficientNetV2 Model & Loss Chart

	precision	recall	f1-score	support
benign	0.93	0.99	0.96	136
malignant	0.98	0.93	0.96	139
accuracy			0.96	275
macro avg	0.96	0.96	0.96	275
weighted avg	0.96	0.96	0.96	275

Figure 5.3.6: EfficientNetV2 Model Performance

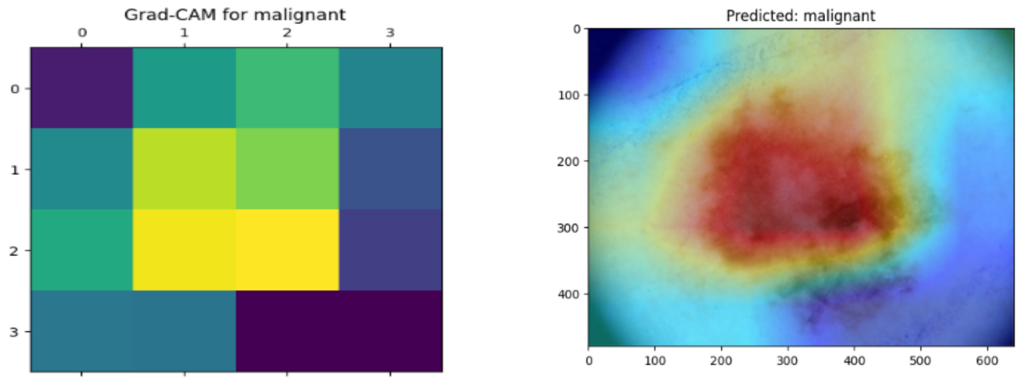

Figure 5.3.7: EfficientNetV2 Grad-CAM Heatmap

Swin Transformer:

The accuracy and loss of our Swin Transformer model after training the model with ISIC 2019-2020 melanoma skin cancer dermoscopic images are,

Accuracy: 96.36%

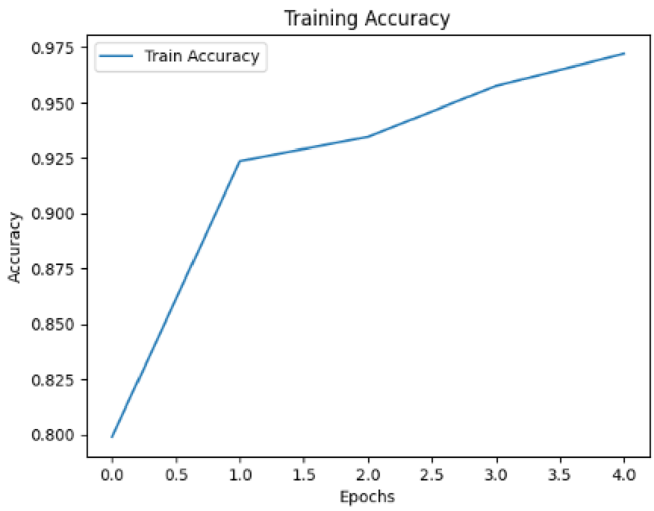

Figure 5.3.8: Swin Transformer Accuracy chart

	precision	recall	f1-score	support
benign	0.95	0.99	0.97	140
malignant	0.98	0.94	0.96	135
accuracy			0.96	275
macro avg	0.96	0.96	0.96	275
weighted avg	0.96	0.96	0.96	275

Figure 5.3.9: Swin Transformer Model Performance

Some Predicted Images:

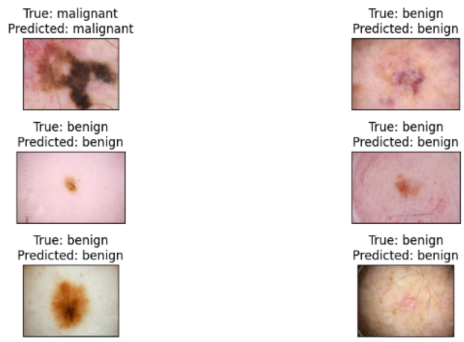

Image prediction:

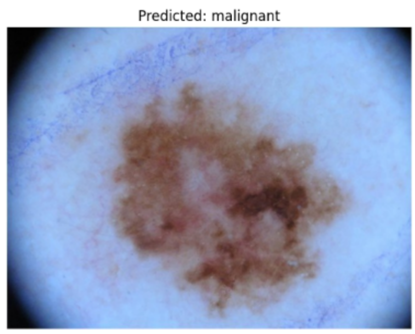

Figure 5.3.10: Some random image predictions in Swin Transformer

ConvNeXt:

The accuracy and loss of our ConvNeXt model after training it with ISIC 2019-2020 melanoma skin cancer dermoscopic images are,

Accuracy: 97.45%

Loss: 0.09097

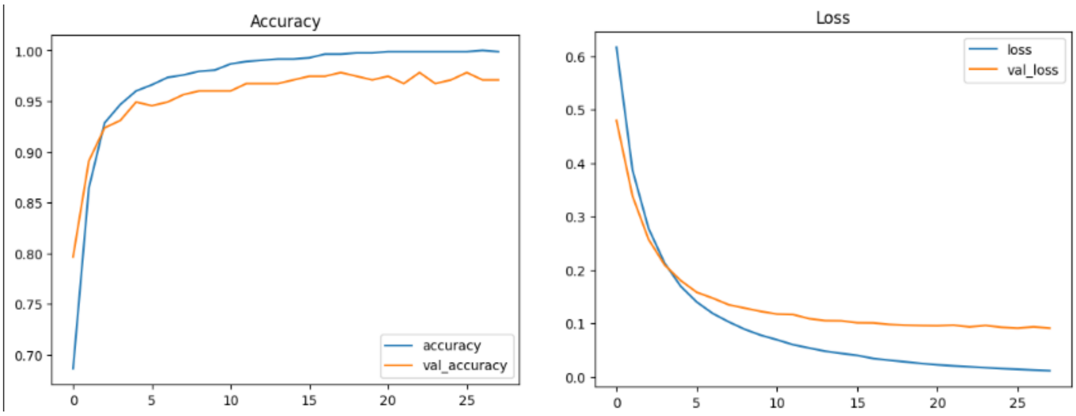

Figure 5.3.11: ConvNeXt Accuracy & Loss Chart

	precision	recall	f1-score	support
benign	0.95	0.98	0.97	124
malignant	0.99	0.96	0.97	151
accuracy			0.97	275
macro avg	0.97	0.97	0.97	275
weighted avg	0.97	0.97	0.97	275

Figure 5.3.12: ConvNeXt Model Performance

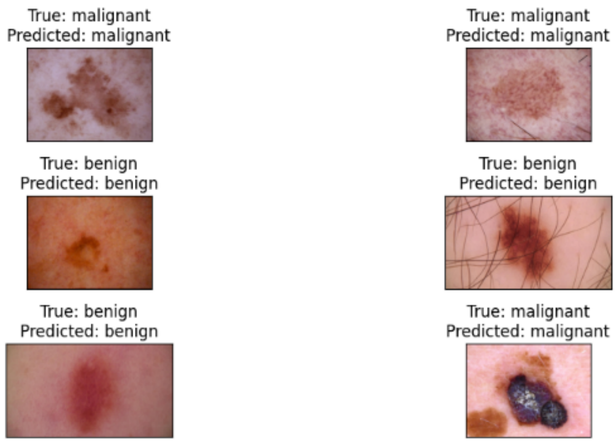

Figure 5.3.13: Some Random image predictions in ConvNeXt

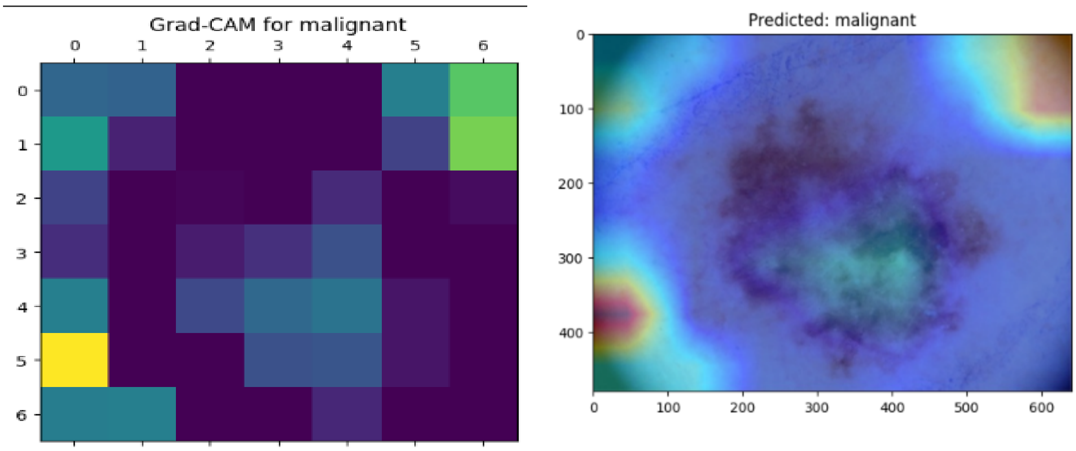

Figure 5.3.14: ConvNeXt Grad-CAM heatmap

VGG16:

The accuracy and loss of our VGG16 model after training it with ISIC 2019-2020 melanoma skin cancer dermoscopic images are,

Accuracy: 90.02%

Loss: 0.3091

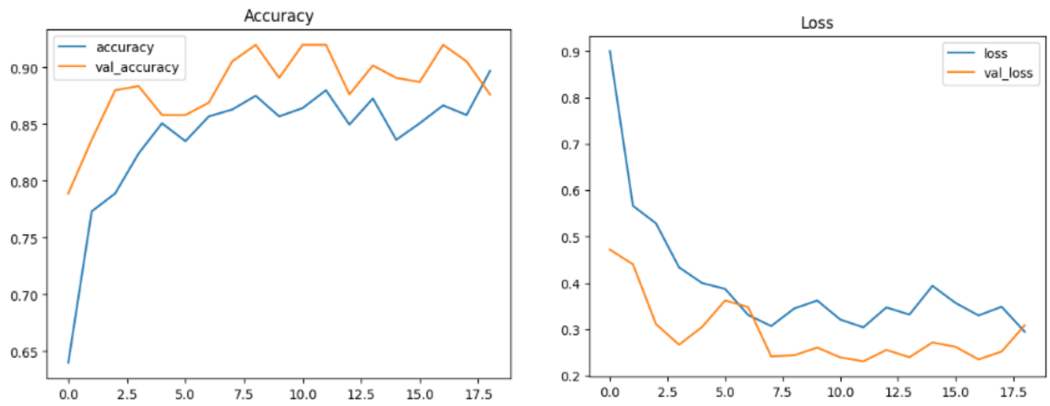

Figure 5.3.15: VGG16 Accuracy & Loss chart

	precision	recall	f1-score	support
benign	0.85	0.93	0.89	137
malignant	0.92	0.83	0.87	138
accuracy			0.88	275
macro avg	0.88	0.88	0.88	275
weighted avg	0.88	0.88	0.88	275

Figure 5.3.16: VGG16 Model Performance

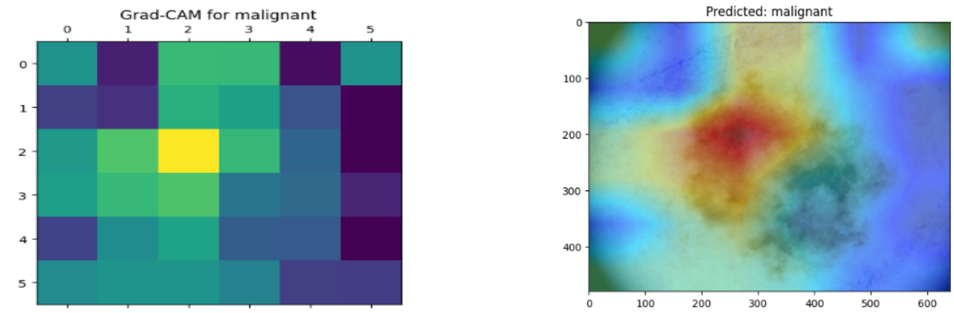

Figure 5.3.17: VGG16 Grad-CAM heatmap

MobileNetV3:

The accuracy and loss of our MobileNetV3 model after training it with ISIC 2019-2020 melanoma skin cancer dermoscopic images are,

Accuracy: 94.91%

Loss: 0.22665

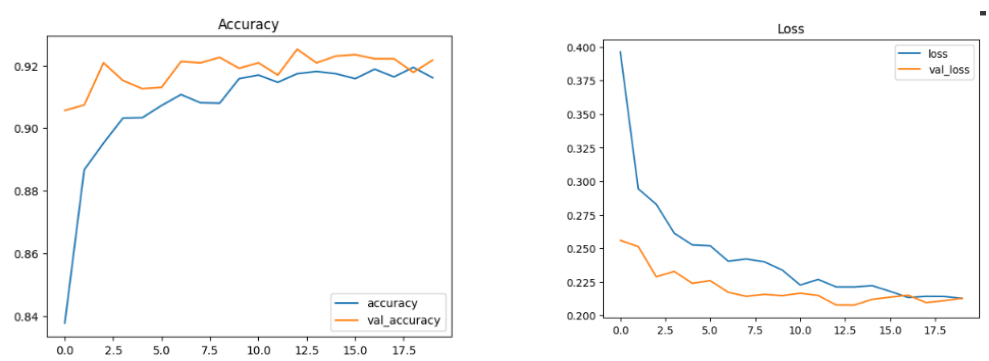

Figure 5.3.18: MobileNetV3 Accuracy & Loss chart

	precision	recall	f1-score	support
benign	0.87	0.99	0.93	1311
malignant	0.98	0.81	0.89	989
accuracy			0.91	2300
macro avg	0.93	0.90	0.91	2300
weighted avg	0.92	0.91	0.91	2300

Figure 5.3.19: MobileNetV3 Model Performance

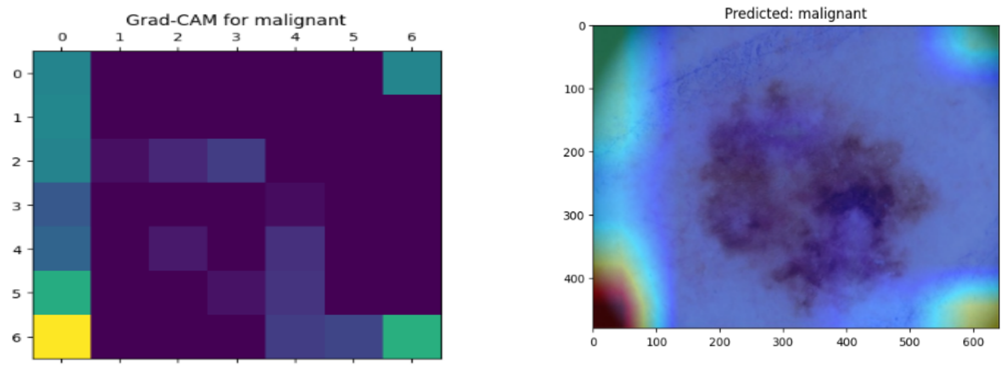

Figure 5.3.20: MobileNetV3 Grad-CAM heatmap

5.4 Summary

Here in this chapter, we discuss what we consider in experimental aspects to train our models, how they are working, and how we evaluate their performance. We show different performance diagrams of our model to show and evaluate its performance. We also show some of our cancer image prediction here to validate the prediction, and we also used the Grad-CAM heatmap, which marks the affected areas of the skin with red, yellow, green, and blue colors. Red prefers highly affected areas, yellow prefers medium affected areas, and green and blue prefer highly affected areas.

CHAPTER 6
IMPACT ON SOCIETY, ENVIRONMENT AND SUSTAINABILITY

6.1 Impact on Life

Current diagnostic methods are time-consuming and prone to human error, which requires more precise and effective detection methods. Our model aims to improve the accuracy of advanced image processing with deep learning techniques, which could facilitate early intervention and potentially life-saving treatments. With our studies, melanoma detection has profound implications for various aspects of healthcare and society. Here’s an overview of the potential impacts of your research:

Early Detection and Treatment:
Early detection of melanoma can increase chances of successful treatment. With this procedure and tools, we can identify melanoma with high accuracy and better patient outcomes.

Minimized Human Error: Traditional diagnostic methods are prone to human error, which can lead to misdiagnosis and delayed treatment. Your deep learning model offers a more precise and consistent approach, reducing the likelihood of diagnostic errors.

Cost-Effectiveness: This development can reduce diagnostic costs. This automated detection model can make skin cancer screening more affordable and accessible to a larger population.

Peace of Mind: Accurate and quick diagnosis can alleviate the anxiety and uncertainty associated with waiting for traditional diagnostic results

6.2 Impact on Society & Environment

By enhancing accuracy, reducing diagnostic time, and making advanced diagnostic tools accessible to a broader audience, your work can lead to earlier detection, better treatment outcomes, and ultimately, save lives. So this study can broadly help our society & environment. Such as,

Web-Based Application: By creating a web-based application for cancer prediction, our research makes advanced diagnostic tools accessible to a wider audience, and patients in remote areas or underserved regions can easily check up and take action.

Patient Empowerment: Providing patients with a reliable tool for early skin cancer detection can empower them to take proactive steps in their healthcare. Early detection leads to better treatment options and improved survival rates, ultimately enhancing the quality of life for patients.

Training Tool for Medical Professionals: The model can be used as an educational tool to train medical students and practitioners, enhancing their diagnostic skills and knowledge about melanoma.

6.3 Ethical Aspects

This development is not just reduces time consumption and human error, but also it maintains patient privacy and data Security, data usage consent, transparency, user education, cost considerations, accessibility, and equity, which are ethical for every patient all over the world. Such as,

Patient Privacy and Data Security: The ISIC 2019-2020 melanoma dataset contains sensitive patient information. But our system does not save any personal patient data. Personal testing image data would be removed or obscured to prevent the possibility of re-identification.

Data Usage Consent: It is important to ensure that the data used in the research was collected with informed consent from the patients. And also, we are not using the patient testing data. The ISIC 2019-2020 melanoma dataset is open for research purposes, so this will not hamper our patient privacy.

User Education: Users should be aware that the model is a tool to assist in diagnosis and not a substitute for professional medical judgment.

Accessibility and Equity:

Ensuring that the web-based application and the diagnostic tool are accessible to all, including underserved and remote populations, is essential.

Cost Considerations:

Keeping the costs associated with using the diagnostic tool affordable is important to ensure that everyone can afford this tool at low cost.

6.4 Sustainability Plan

For the best sustainability, we planned for some steps, that will provide us with sustainability, technical sustainability, operational sustainability, environmental sustainability, and social sustainability. Such as,

Partnerships with Healthcare Institutions: We are already trying to collaborate with hospitals, clinics, and dermatology centers to integrate the model into their diagnostic processes.

Commercialization: By licensing the technology as medical device companies and developing a business model that includes subscription services.

Continuous Model Improvement: We are trying to implement a continuous learning system where the model can regularly update and improve its accuracy.

Open-Source Collaboration: Already Our dataset is open-source, which is provided by ISIC 2019-2020.

Training and Support for Users: In the future, we will develop comprehensive training programs for clinicians and healthcare staff to ensure they can effectively use this model.

Paperless Operations: Promote digital documentation and communication to reduce paper use.

Patient Education: Create educational materials to help patients understand the benefits and limitations of the model. Promote awareness about the importance of early detection and regular skin checks.

6.5 Summary

At this time, diagnostic methods are time-consuming and prone to human error, which requires more precise and effective detection methods. With our studies, melanoma detection has profound implications for various aspects of healthcare and society. Our development is potentially impactful in our lives, with many steps like Early Detection and Treatment, Minimized Human Error, Cost-Effectiveness, and Peace of Mind for patients. And it's efficiently impactful on our society and environment. Also, it maintains our daily life security through an ethical approach. For best sustainability, we planned some steps, which will provide us with financial sustainability, Technical Sustainability, Operational Sustainability, Environmental Sustainability, and Social Sustainability.

CHAPTER 7
CONCLUSION AND FUTURE WORK

7.1 Conclusions

Overall, we evaluate the performance of different deep-learning architectures in accurately classifying skin lesions. Our experiments demonstrate that the ConvNeXt and Swin Transformer models achieved the highest accuracy, with ConvNeXt achieving 97.45% and Swin Transformer achieving 96.36%. We analyze the reasons behind the superior performance of these models, considering factors such as model architecture and training strategies. They all performed well with significant accuracy. But among all these 6 models, ConvNeXt and Swin Transformer performed best with 97.45% accuracy and 96.36% accuracy, respectively. The reasons for their strong performance can be attributed to several factors related to their architecture and design principles. The dataset comprised high-resolution images of skin lesions, categorized into benign and malignant classes. Images were preprocessed to ensure uniformity in size and quality, with transformations such as resizing, normalization, and augmentation. To assess model performance, we employed a range of evaluation metrics, including accuracy, precision, recall, F1-score, and support. If the difference between test accuracy and validation accuracy is too high, then the model is considered overfitting. Also, precision, recall, f1-score, and support of a model provide a brief description of the model and how well it is performing. These metrics provided a comprehensive understanding of each model's ability to correctly classify skin lesions. The experiments were conducted using a high-performance computing environment, leveraging GPUs to accelerate model training. The models were implemented using popular deep learning frameworks such as TensorFlow and PyTorch, ensuring the scalability and reproducibility of the experiments. For the best performance, we are comparing all of our model's generated predictions to produce a final and more accurate prediction.

7.2 Further Suggested Works

In the future, we can implement so many efficient features, like, Integrating histopathological images, combining dermoscopic images with patient data, being self-supervised, AI describing features, etc.

1. Integrate histopathological images along with dermoscopic images for a comprehensive analysis.
2. Combine dermoscopic images with patient clinical data (age, gender, and medical history) to improve model performance.
3. Implement self-supervised learning techniques to leverage unlabeled data.

4. Add AI Describe features based on our model predictions.

7.3 Limitations

We are using the ISIC 2019-2020 melanoma skin cancer image dataset in our paper to train our model and do the prediction. ISIC is an open-source platform that gathers and stores skin cancer images from different sources, providing high-quality data to advance the detection and diagnosis of skin cancer through AI and other computational methods, but we weren't able to collect melanoma skin cancer data by ourselves from our regions, which is one of the biggest limitations for us here in this research. Collecting data from the local community gives us knowledge about the people of the country, which gives us a great opportunity to work for the local people and provide them with a good solution for their skin cancer illness. That would also be a great milestone in our motivation for this research paper. We are using our dataset to train CNN models to predict the result, but CNNs can easily overfit the training data, especially when the dataset is small or not diverse enough. This leads to poor generalization of unseen data. CNNs typically require large amounts of labeled data to achieve good performance. This can be a significant limitation in domains where labeled data is scarce or expensive to obtain. If the dataset is imbalanced (significantly more benign lesions than malignant ones), the model may become biased toward the more frequent classes.

References:

[1] J. Daghrir, L. Tlig, M. Bouchouicha, and M. Sayadi, “Melanoma skin cancer detection using deep learning and classical machine learning techniques: A hybrid approach,” 2020 5th International Conference on Advanced Technologies for Signal and Image Processing (ATSIP). IEEE, Sep. 2020. doi: 10.1109/atsip49331.2020.9231544.

[2] Md. A. Hossin, F. F. Rupom, H. R. Mahi, A. Sarker, F. Ahsan, and S. Warech, “Melanoma Skin Cancer Detection Using Deep Learning and Advanced Regularizer,” 2020 International Conference on Advanced Computer Science and Information Systems (ICACSIS). IEEE, Oct. 17, 2020. doi: 10.1109/icacsis51025.2020.9263118.

[3] K. M. Hosny, M. A. Kassem, and M. M. Foaud, “Skin Cancer Classification using Deep Learning and Transfer Learning,” 2018 9th Cairo International Biomedical Engineering Conference (CIBEC). IEEE, Dec. 2018. doi: 10.1109/cibec.2018.8641762.

[4] Y. Li and L. Shen, “Skin Lesion Analysis towards Melanoma Detection Using Deep Learning Network,” Sensors, vol. 18, no. 2. MDPI AG, p. 556, Feb. 11, 2018. doi: 10.3390/s18020556.

[5] N. Zhang, Y.-X. Cai, Y.-Y. Wang, Y.-T. Tian, X.-L. Wang, and B. Badami, “Skin cancer diagnosis based on optimized convolutional neural network,” Artificial Intelligence in Medicine, vol. 102. Elsevier BV, p. 101756, Jan. 2020. doi: 10.1016/j.artmed.2019.101756.

[6] N. Rezaoana, M. S. Hossain, and K. Andersson, “Detection and Classification of Skin Cancer by Using a Parallel CNN Model,” 2020 IEEE International Women in Engineering (WIE) Conference on Electrical and Computer Engineering (WIECON-ECE). IEEE, Dec. 26, 2020. doi: 10.1109/wiecon-ece52138.2020.9397987.

[7] M. Hasan, S. D. Barman, S. Islam, and A. W. Reza, “Skin Cancer Detection Using Convolutional Neural Network,” Proceedings of the 2019 5th International Conference on Computing and Artificial Intelligence. ACM, Apr. 19, 2019. doi: 10.1145/3330482.3330525.

[8] M. F. Jojoa Acosta, L. Y. Caballero Tovar, M. B. Garcia-Zapirain, and W. S. Percybrooks, “Melanoma diagnosis using deep learning techniques on dermatoscopic images,” BMC Medical Imaging, vol. 21, no. 1. Springer Science and Business Media LLC, Jan. 06, 2021. doi: 10.1186/s12880-020-00534-8.

[9] M. Vidya and M. V. Karki, “Skin Cancer Detection using Machine Learning Techniques,” 2020 IEEE International Conference on Electronics, Computing and Communication Technologies (CONECCT). IEEE, Jul. 2020. doi: 10.1109/conecct50063.2020.9198489.

[10] MA. A. Thaajwer and UA. P. Ishanka, “Melanoma Skin Cancer Detection Using Image Processing and Machine Learning Techniques,” 2020 2nd International Conference on Advancements in Computing (ICAC). IEEE, Dec. 10, 2020. doi: 10.1109/icac51239.2020.9357309.

[11] M. Tahir, A. Naeem, H. Malik, J. Tanveer, R. A. Naqvi, and S.-W. Lee, “DSCC_Net: Multi-Classification Deep Learning Models for Diagnosing of Skin Cancer Using Dermoscopic Images,” Cancers, vol. 15, no. 7. MDPI AG, p. 2179, Apr. 06, 2023. doi: 10.3390/cancers15072179.

[12] S. Haggenmüller et al., “Federated Learning for Decentralized Artificial Intelligence in Melanoma Diagnostics,” JAMA Dermatology. American Medical Association (AMA), Feb. 07, 2024. doi: 10.1001/jamadermatol.2023.5550.

[13] M. M. Yaqoob et al., “Symmetry in Privacy-Based Healthcare: A Review of Skin Cancer Detection and Classification Using Federated Learning,” Symmetry, vol. 15, no. 7. MDPI AG, p. 1369, Jul. 05, 2023. doi: 10.3390/sym15071369. Muhammad Mateen Yaqoob 1ORCID,Musleh Alsulami 2,*ORCID,Muhammad Amir Khan 1,3ORCID,Deafallah Alsadie 2,Abdul Khader Jilani Saudagar 4ORCID,Mohammed AlKhathami 4ORCID andUmar Farooq Khattak 5,*(5 July 2023).Symmetry in Privacy-Based Healthcare: A Review of Skin Cancer Detection and Classification Using Federated Learning.

[14] D. Bi, D. Zhu, F. R. Sheykhahmad, and M. Qiao, “Computer-aided skin cancer diagnosis based on a New meta-heuristic algorithm combined with support vector method,” Biomedical Signal Processing and Control, vol. 68. Elsevier BV, p. 102631, Jul. 2021. doi: 10.1016/j.bspc.2021.102631.

[15] G. Reshma1, Chiai Al-Atroshi, Vinay Kumar Nassa, B.T. Geetha, Gurram Sunitha, Mohammad Gouse Galety, S. Neelakandan., 2022, November. Deep Learning-Based Skin Lesion Diagnosis Model Using Dermoscopic Images.

[16] Kalyani Chapa, Kola Varsha, Mayakuntla Vamsi Krishna, Manyam Viswa Bhavitha, and Kilana Leela Deepak, "Deep Learning Model for Accurate Classification of Skin Cancer using Dermoscopic Images," International Journal of Advanced Research in Science, Communication, and Technology. Naksh Solutions, pp. 65–73, Apr. 26, 2023. doi: 10.48175/ijarsct-9474.

[17] Agbley, B. L. Y., Li, J., Haq, A. U., Bankas, E. K., Ahmad, S., Agyemang, I. O., Kulevome, D., Ndiaye, W. D., Cobbinah, B., & Latipova, S. (2021). Multimodal melanoma detection with federated learning. 2021 18th International Computer Conference on Wavelet Active Media Technology and Information Processing (ICCWAMTIP)

[18] Malo, D. C., Rahman, M. M., Mahbub, J., & Khan, M. M. (2022). Skin cancer detection using convolutional neural network. 2022 IEEE 12th Annual Computing and Communication Workshop and Conference (CCWC), 0169–0176.

[19] Chabi Adjobo, E., Sanda Mahama, A. T., Gouton, P., & Tossa, J. (2019). Proposition of convolutional neural network based system for skin cancer detection. 2019 15th International Conference on Signal-Image Technology & Internet-Based Systems (SITIS), 35–39.

[20] H. M. Balaha and A. E.-S. Hassan, "Skin cancer diagnosis based on deep transfer learning and sparrow search algorithm," Neural Computing and Applications, vol. 35, no. 1. Springer Science and Business Media LLC, pp. 815–853, Sep. 23, 2022. doi: 10.1007/s00521-022-07762-9.

[21] Y. Li and L. Shen, "Skin Lesion Analysis towards Melanoma Detection Using Deep Learning Network," Sensors, vol. 18, no. 2. MDPI AG, p. 556, Feb. 11, 2018. doi: 10.3390/s18020556.

[22] Dataset obtained from https://www.kaggle.com/datasets/sallyibrahim/skin-cancer-isic-2019-2020-malignant-or-benign

Appendix A

Course Outcomes, Complex Engineering Problems (EP) and Complex Engineering Activities (EA) Addressing

Title: Early Melanoma Skin Cancer Detection by Processing Dermoscopic Images Using Traditional Deep-learning Models.

Student ID: 201-15-3470 & 201-15-3294

CO Description for FYDP

CO	CO Descriptions	PO
Phase -I		
CO1	Integrate recently gained and previously acquired knowledge to identify a melanoma skin cancer detection problem for the Final Year Design Project (FYDP)	**PO1**
CO2	Analyze different aspects of the goals in designing a solution for this FYDP	**PO2**
CO3	Explore diverse problem domains through a literature review, delineate the issues, and establish this goals for the FYDP	**PO4**
CO4	Perform economic evaluation and cost estimation and employ suitable project management procedures throughout the development life cycle of the FYDP	**PO11**

Phase -II		
CO5	Design and develop technical solutions and system components or processes that meet specified requirements, ensuring compliance with public health and safety standards, as well as considering cultural, socioeconomic, and environmental factors in this FYDP	**PO3**
CO6	Choose and apply appropriate methodologies, resources, and contemporary engineering and IT technologies to address complex engineering processes, encompassing prediction and modeling, while adhering to relevant constraints in this FYDP	**PO5**
CO7	Analyze societal, health, safety, legal, and cultural considerations, along with associated responsibilities, in the context of professional engineering practice and the resolution of this problem, employing logical reasoning guided by contextual understanding.	**PO6**
CO8	Comprehend and evaluate the enduring sustainability and impact of professional engineering endeavors in addressing intricate engineering challenges within social and environmental frameworks.	**PO7**
CO9	Implement ethical principles and adhere to professional standards and norms in this FYDP	**PO8**
CO10	Capable of operating proficiently both individually and as a team member or leader across diverse teams and interdisciplinary settings in this FYDP.	**PO9**

CO11	Proficiently communicate with the engineering community and broader society regarding complex engineering endeavors, including the ability to comprehend and generate comprehensive reports and design documentation, as well as provide and receive clear instructions throughout this FYDP.	**PO10**
CO12	Acknowledge the importance of self-directed and life-long learning within the evolving landscape of technology, and possess the readiness and capability to engage in lifelong learning endeavors.	**PO12**

Addressing CO (1 to 8), Knowledge Profile (K), Attainment of Complex Engineering Problems (EP), and Attainment of Complex Engineering Activities (EA)

Addressing CO (1 to 8), Knowledge Profile (K), Attainment of Complex Engineering Problems (EP):

SN	EP Definition	Attainment	CO	Justification (with Knowledge Profile)	References
1.	EP1: Depth of Knowledge required	Yes	CO1, CO2, CO3, CO5, CO6, CO7 and CO8	This project demonstrates fundamental engineering (K3) principles by employing deep neural networks, data augmentation techniques, and diverse CNN architectures for image processing and classification tasks. In this project we used CNN architectures like ResNet50, VGG16, ConvNeXt, MobileNetV3, Swin Transformer and EfficientNetV2 to do detection melanoma skin cancer using dermoscopic images, crucial for computer-aided diagnosis.	Page no: [13-19] Section: [4.1-4.2] Page no: [3] Section: [1.4] Page no: [3-4] Section: [1.5]

				The project applies engineering practice & design (K5) by the figure of process of experiments. The project addresses engineering practice & technology (K6) by employing CNN model.	Page no: [10] Section: [3.1] Page no: [23] Section: [5.1]
				This project ensures to K8 (Research Literature) by synthesizing insights from recent studies, to advance melanoma skin cancer detection using deep learning, showcasing a comprehensive understanding of current methodologies.	Page no: [6-9] Section: [2.2, 2.3]

2.	EP2: Range of Conflicting Requirements	Yes	CO2, and CO7	This project addresses EP-2 by showing obstacles in melanoma skin cancer detection, including limitations of traditional methods and the complexities of integrating deep CNNs. Through comparative analysis, it confronts challenges in understanding spatial distributions, offering insights for refining diagnostic methodologies.	Page no: [3] Section: [1.3] Page no: [3-4] Section: [1.5]
3.	EP3: Depth of analysis required	Yes	CO2, and CO6	This project addresses EP-3 by meticulously comparing experimental outcomes, highlighting Deep Learning CNN models as the chosen significant solution for enhancing skin cancer detection by comparing models detected classes.	Page no: [13] Section: [4.1] Page no: [20-21] Section: [4.3]

4.	EP4: Familiarity of Issues	Yes	CO8	This project uses knowledge from different fields, not just computer science and engineering. It helps improve medical tests for skin cancer, leading to better public health and healthcare practices. which indicates EP-4.	Page no: [3-4] Section: [1.5] Page no: [6-8] Section: [2.2]
5.	EP5: Extends of application codes	No	CO5	N/A	N/A
6.	EP6: Extends of stakeholders involved and conflicting requirements	No	CO8	N/A	N/A

7.	EP7: Interdependence	Yes	CO5	This project tackles big problems by combining different parts like data collection, statistical analysis, and proposed methods. This way, it creates a complete solution for tough issues in medical diagnostics, meeting EP-7 standards.	Page no: [10-11] Section: [3.2] Page no: [23-31] Section: [5.1,5.2,5.3]

Plagiarism Report:

EARLY MELANOMA SKIN CANCER DETECTION BY PROCESSING DERMOSCOPIC IMAGES USING TRADITIONAL DEEP-LEARNING MODELS.pdf

ORIGINALITY REPORT

15%	12%	5%	8%
SIMILARITY INDEX	INTERNET SOURCES	PUBLICATIONS	STUDENT PAPERS

PRIMARY SOURCES

1	Submitted to Daffodil International University Student Paper	2%
2	www.ijcert.org Internet Source	2%
3	www.semanticscholar.org Internet Source	1%
4	Submitted to Liverpool John Moores University Student Paper	1%
5	Submitted to University of Leeds Student Paper	1%
6	www.codewithc.com Internet Source	1%
7	Submitted to Student Paper	<1%
8	Submitted to University of Computer Studies Student Paper	<1%