AN ADVANCED CONVOLUTIONAL NEURAL NETWORK FOR SKIN DISEASE DETECTION

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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

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APPROVAL

This Project titled "An Advanced Convolutional Neural Network For Skin Disease Detection", submitted by **Anamika Roy** and **Shanjana Tanjim Shamonti** 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 15/07/2024.

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DECLARATION

We hereby declare that this project has been done by us under the supervision of **Mayen Uddin Mojumder, Senior Lecture, 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.

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ABSTRACT

This study refers to an advanced convolutional neural network (CNN) approach for detecting skin diseases, with a focus on distinguishing between cancerous and non-cancerous conditions. Using Kaggle's 'Melanoma Skin Cancer Dataset', we addressed class imbalance with rigorous data augmentation, resulting in a balanced dataset of 5000 images per class. Our proposed multilayer CNN architecture was designed and trained using this balanced dataset, with the goal of achieving high disease classification accuracy. To evaluate our approach, we compared our custom CNN architecture to four popular pretrained models: VGG16, ResNet101, InceptionV3, and MobileNetV2. After extensive experimentation and evaluation, we discovered that MobileNetV2 consistently outperformed all other models, achieving an impressive 98.95% accuracy. This result highlights the effectiveness of MobileNetV2 in accurately detecting skin diseases. This result shows MobileNetV2's effectiveness in accurately detecting skin diseases, which outperforms even our proposed CNN architecture. These findings focus on the importance of selecting the right model architecture for skin disease detection tasks. The superior performance of MobileNetV2 shows its suitability for real-world applications requiring accurate and efficient disease diagnosis. Overall, this study adds valuable insights to the development and evaluation of CNN-based approaches for skin disease detection, with implications for improving diagnostic accuracy and patient outcomes.

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CHAPTER 1
INTRODUCTION

1.1 Overview

Skin cancer is one of the most prevalent diseases worldwide, with melanoma being the deadliest. Early detection and diagnosis are critical to successful treatment and patient outcomes. In recent years, advancements in artificial intelligence (AI) and deep learning have shown great promise in automating the process of skin disease detection, potentially augmenting physicians' diagnostic capabilities and increasing access to timely healthcare T. A. Rimi, N. Sultana et al.2020 [1] Convolutional neural networks (CNNs) have become known as effective tools for image classification, such as skin disease detection. CNNs can analyze dermatological images and accurately detect signs of cancer or other abnormalities by leveraging their ability to learn discriminative features from raw pixel data. However, factors such as dataset class imbalance, architectural design choices, and the availability of large-scale labeled data can all have an impact on CNN-based system performance Ottom, Mohammad Ashraf et al. 2019 [3] In this study, we use an advanced CNN approach to solve the problem of detecting skin diseases. We begin by curating an extensive dataset using Kaggle's 'Melanoma Skin Cancer Dataset', which contains a diverse range of images of skin lesions labeled as cancerous or non-cancerous. To reduce class imbalance and improve model generalization, we use rigorous data augmentation techniques, resulting in a balanced dataset with equal representation of both classes Gautam, Vinay, et al. 2023[4] We want to create a model that can accurately distinguish between cancerous and non-cancerous lesions, which will help with early diagnosis and treatment planning. In addition, we compare the performance of our proposed CNN architecture to four pretrained models: VGG16, ResNet101, InceptionV3, and MobileNetV2. Through rigorous experimentation and evaluation, we look to identify the most effective model architecture for this critical task Saifan, Ramzi, et al. 2022 [7].

Our study, which makes use of deep learning and CNNs, contributes to ongoing efforts to improve the accuracy and efficiency of skin disease diagnosis, ultimately improving patient outcomes and healthcare access.

1.2 Background and Present State

Before starting the project, a thorough literature review will be conducted to better understand existing methodologies, challenges, and advances in skin disease detection using convolutional neural networks (CNNs). Data collection and preprocessing procedures will be discussed, with a focus on obtaining a diverse and carefully selected dataset of skin lesion images. Ethical concerns, such as patient data privacy and model fairness, will be addressed in accordance with established policies. Technical infrastructure, including hardware and software requirements, will be built to support model development and training. In addition, project timelines, milestones, and deliverables will be defined to ensure clear objectives and progress tracking throughout the project's duration. These preliminary steps will lay the groundwork for a successful research project that meets its objectives.

1.3 Problem Statement

The rising incidence of skin cancer underscores the need for accurate and timely diagnosis to improve patient outcomes. However, manual diagnosis is subjective, time-consuming, and may vary among dermatologists. Leveraging the capabilities of deep learning and CNNs, this study aims to develop an automated system for skin disease detection. By addressing challenges such as class imbalance and selecting appropriate model architectures, we seek to enhance the accuracy and efficiency of diagnosis while minimizing the reliance on human interpretation. Furthermore, by comparing the performance of our proposed CNN architecture with pretrained models, we aim to identify the most effective approach for skin cancer detection. Finally, the goal of this research is to contribute to the development of automated healthcare solutions that can supplement dermatologists' diagnostic capabilities and improve skin cancer patients' access to timely treatment.

1.4 Objective

Skin cancer, in particular melanoma, is a significant global health risk, and early detection is important for successful treatment. However, manual diagnosis by medical professionals can be time-consuming and subject to inter-observer variability. We hope to create an automated system for detecting skin diseases by leveraging advances in deep learning and convolutional neural networks (CNN). By using AI, we hope to provide dermatologists with a dependable tool that can aid in the early detection of cancerous lesions, resulting in prompt intervention and better patient outcomes. Furthermore, we address issues such as class imbalance and model selection in order to improve the accuracy and efficiency of skin disease diagnosis while reducing the burden on healthcare professionals. Through this work, we hope to contribute to the development of readily available scalable, and accurate skin cancer detection solutions, ultimately saving lives and improving public health.

1.5 Scope and Limitations

The main focus of this study is the design and comparison of CNN based approaches in skin disease diagnosis and emphasis is on differentiating cancerous and non-cancerous lesions. It covers balancing the classes by augmenting the data, comparing different deep learning architectures such as CNN and evaluating the results in terms of accuracy, precision, recall, and F1 Score. Still, there are some biases in this study due to the limited dataset from the Kaggle; the study may not present all possible skin lesions in the clinic. Furthermore, although model evaluation is performed to assess their performance, clinical solutions' validation along with real-world deployment are outside the scope of this paper. The study also assumes ethical compliance and data privacy which is an important area that needs more emphasis in the practical application.

1.6 Report Organization

The proposed report is structured in a comprehensive manner that walks readers through the research process, findings, and implications. Each chapter serves an individual purpose, resulting to the document's overall structure and depth. Chapter 1: Introduction, Gives an overview of the research topic, goals, and motivation for the study. Explains the scope and importance of the research problem. Chapter 2: Literature, Reviews relevant literature, theories, and previous research on skin disease classification, deep and transfer learning techniques. Chapter 3: Research Methodology, Describes the study's methodology, which includes data collection, preprocessing, model selection, training, and evaluation procedures. Chapter 4: Experimental Results, Presents the findings and results of the experiments, such as performance metrics, transfer learning model comparisons, and classification accuracy analyses. Chapter 5: The Impact on Society, Discusses the potential societal implications and applications of the study's findings, focusing on the importance of automated disease detection in medical field. Chapter Six: Conclusion, and Implications for Future Research, Summarizes the study's key findings, draws conclusions based on the results, makes recommendations for future research directions, and discusses the research's broader implications in the field of medicine.

1.7 Summary

The introduction chapter provides a rationale of early and accurate diagnosis of skin diseases especially melanoma to enhance patient's survival and decrease mortality index. It also turns the focus to the shortcoming of manual diagnosis by dermatologist such as time consuming and inter-observer actual variance. The use of deep learning, particularly CNNs, is a viable approach for automating skin diseases' diagnosis. The solution of the proposed study is to design a multilayer CNN architecture with the augmentation and a balanced dataset. This research compares this proposed architecture with four pretrained models, namely VGG16, ResNet101, InceptionV3, and MobileNetV2 to ascertain the best method. The hope is that by incorporating these sophisticated techniques, the authors shall improve diagnostic results, thus promoting improved skin cancer diagnostic tools in the field of health care delivery.

CHAPTER 2

LITERATURE REVIEW

2.1 Overview

The literature investigation outlines today's progress and issues with skin disease detection as an extension of convolutional neural networks (CNNs). Discussions start with the oversight of the original works that demonstrate the effectiveness of CNNs in image classification and practical use in solving dermatological problems. The review then examines the different architectures of CNN which include; VGG16, ResNet101, InceptionV3, and MobileNetV2, arguing its suitability in skin lesion classification. It also explains the problem of class imbalance and how the techniques of data augmentation help to improve the model resilience. In addition, the review addresses the ethical issues including patient data privacy and model fairness and stressed on these aspects while discussing about the practical applications. Therefore, the literature review of the current paper offers an integrated view of the state of the art and suggests more directions for the further study of the AI-based skin disease diagnostics.

2.2 Related Works

In this literature review, we look at the changing landscape of skin disease detection, specifically advancements in convolutional neural network (CNN) models and their use in dermatological diagnosis. We review recent research on CNN architectures, data augmentation techniques, and model evaluation metrics for accurate lesion classification. In addition, we look into the ethical considerations and societal implications of deploying AI-driven diagnostic systems in dermatology. By combining current research findings, this review aims to provide insights into modern methods and future directions for improving skin disease diagnosis with CNNs. As given below, I am writing a similar paper review, which will help me more:

T. A. Rimi, N. Sultana et al. [1] presented a prototype that uses convolutional neural networks (CNNs) to identify a range of skin conditions, including ulcers, lichen simplex, skin infection hand, eczema hand, eczema subacute, and stasis dermatitis. CNNs were selected because they performed better in image classification tasks than deep neural networks (DNNs). In this study, images are processed to train the CNN model to classify different skin conditions. This research lies at the nexus of image processing techniques and machine learning. The attainment of a 73% precision rate on a 500-image dataset from dermnet indicates encouraging outcomes, suggesting the possibility of additional enhancements with more extensive datasets. This method shows promise for improving the use of neural networks in the early detection and diagnosis of skin diseases. Convolutional Neural Network (CNN) architectures, such as MobileNet and Xception, to present an effective skin disease recognition solution used R. Sadik, A. Majumder et al. [2]. For better performance, the CNN models were enhanced with extra features through transfer learning from the Imagenet dataset. In order to create a benchmark, the research contrasts several CNN architectures, including ResNet50, InceptionV3, Inception-ResNet, and DenseNet, showing the effectiveness of augmentation and transfer learning methods. The effectiveness of the suggested strategy is confirmed by evaluation metrics like accuracy, precision, recall, and F1-score, with MobileNet and Xception achieving 96.00% and 97.00% accuracy, respectively. To further expand the research's useful applications, a web-based architecture for real-time disease recognition was also suggested and put into practice. Ottom, Mohammad Ashraf. et al. [3] used convolutional neural networks to create a predictive model for melanoma detection in particular, which is a type of skin cancer. The first stage is to prepare the image data, which includes edge detection, noise reduction, and classification to separate out important parts for analysis. The suggested method puts into practice a CNN model with four fully connected layers, three max-pooling layers, and three convolutional layers. The model's accuracy of 74% when testing produces positive outcomes. These results highlight the potential for further developments in melanoma online diagnosis, which could result in the creation of a web application for quick and easy diagnosis. Gautam, Vinay, et al. [4] addressed the importance of early skin disease detection in order to reduce the costs and issues of advanced treatment. It draws attention to the limitations of current methods in obtaining precise diagnoses and presents a high-performance Convolutional Neural Network (CNN) for early classification and detection of skin conditions. The process entails preprocessing images of skin diseases, identifying key characteristics, and applying a Deep Convolutional Neural Network (DCNN) for analysis. Offering significant potential for improving early diagnosis and treatment outcomes, the proposed approach successfully identifies six different types of skin diseases with remarkable speed, simplicity, and accuracy of up to 98%. Maduranga, M. W. P. et al. [5] addressed the problem of accurate diagnosis by introducing a mobile AI application that can detect different kinds of skin diseases. To classify diseases, deep learning algorithms leverage Convolutional Neural Networks (CNNs) on the HAM10000 dataset. After thorough analysis, methods based on CNN turn out to be the most efficient for this particular task. The mobile application helps dermatologists and patients alike by providing quick and accurate diagnosis through image analysis of afflicted areas. The suggested method achieves an accuracy of about 85% with much faster region detection and lower computational load than standard models like MobileNet. These results raise the possibility that general practitioners could diagnose skin diseases quickly and accurately using cellphones. Albawi, Saad, et al.[6] presented a novel approach that uses neural networks and region growing techniques for preprocessing and segmentation in order to identify three types of skin diseases: nevus, atypical, and melanoma. A hybrid approach that combines 2D-DWT, geometric, and texture features is used to extract features. The suggested approach, which makes use of Convolutional Neural Networks (CNNs) for classification, scores an impressive 96.768% accuracy on the International Skin Imaging Collaboration (ISIC) dataset. The approach's superiority over current techniques is demonstrated through comparative analysis, highlighting its potential to advance the diagnosis and treatment of skin diseases. Saifan, Ramzi, et al. [7] presented a system that classifies color images of skin lesions across six diseases using convolutional neural networks (CNNs). The model, which makes use of a pre-trained deep CNN, can distinguish between vitiligo, acne, athlete's foot, chickenpox, eczema, and skin cancer with accuracy. Robust training and testing were made possible by the construction of a dataset comprising 3000 colored images from diverse online sources. The experimental results demonstrate the efficacy of the suggested model; it achieves an astounding accuracy of 81.75%, outperforming previous studies in the domain. With 90% of the images used for training and 10% for out-of-sample accuracy testing, the holdout method was employed to validate this accuracy. Bajwa, Muhammad Naseer, et al. [8] used Deep Learning techniques to classify a wide range of skin diseases, along with the utilization of disease taxonomy to improve accuracy, represents an impressive advancement over previous attempts in computer-aided dermatology diagnosis. Utilizing both DermNet and ISIC Archive datasets for Deep Neural Network training, the research sets new benchmarks for accuracy and

Area Under the Curve (AUC) metrics. Notably, the models achieve an impressive 80% accuracy and 98% AUC for 23 diseases on DermNet, and 93% average accuracy and 99% AUC for 7 diseases on ISIC Archive. In addition, the study is the first to classify 622 different sub-classes on DermNet with 67% accuracy and 98% AUC, showing the potential of Deep Learning for diagnosing skin diseases in real time and helping doctors with large-scale screening using clinical or dermoscopic images. Ahmad, Belal, et al [9] presented a hybrid classification approach that combines organized Bidirectional Long Short-Term Memory (BLSTM) networks with deep convolutional neural networks. First, from pictures of faces of skin diseases, deep features are extracted, and then sequential features are learned with a dual BLSTM network. The forward and backward LSTM hidden states are concatenated and fed into a fully connected layer through max-pooling. The softmax function is then used for classification. The method outperforms current state-of-the-art methods in skin disease classification, as demonstrated by evaluation on two skin disease datasets, which provided a mean accuracy of 91.73%. Convolutional neural networks (CNNs) were developed in Yanagisawa, Yuta, et al. [10] with the purpose of segmenting skin images and producing a dataset that could be used for computer-aided diagnosis (CAD) of various skin conditions. Skin and lesion regions were identified and segmented according to specific requirements using a CNN segmentation model based on DeepLabv3+. Atopic dermatitis and malignant diseases, as well as their related complications, could be defined with 90% sensitivity and specificity using the created CNN-segmented image database. CNN segmentation method for CAD applications was found to be effective, as shown by the accuracy of skin disease classification using the CNN-segmented dataset above the original dataset and matching that of manually cropped images. N. Akmalia, P. Sihombing et al. [11] proposed an approach to analyze and classify images of skin diseases based on shape, color, and texture by combining Local Binary Pattern (LBP) and Convolutional Neural Network (CNN) techniques. The method could be used as an automated sensor or visual aid to detect skin conditions early on. The results show the effectiveness of combining LBP with CNN for skin disease classification, with an average accuracy rate of 92%. Additionally, this study offers helpful data for further image processing research and serves as a standard for improvements in the application of CNN and LBP for disease classification. J. Rathod, V. Waghmode, A. Sodha et al. [12] addressed an automated image-based system that uses machine learning classification methods to identify skin diseases. The system evaluates and processes skin images using computational techniques, such as noise reduction and image enhancement. Convolutional Neural Networks (CNNs) are used for feature extraction, and softmax algorithms are used for classification to produce accurate diagnosis reports as the end result. This method is more accurate and produces results more quickly than traditional methods, making it a dependable and effective system for diagnosing dermatological diseases. T. D. Nigat, T. M. Sitote et al. [13] used convolutional neural networks (CNNs) to classify four types of fungal skin diseases: tinea pedis, tinea capitis, tinea corporis, and tinea unguium. Preprocessing procedures, such as image normalization and augmentation, are applied to a dataset containing 407 fungal skin lesions from the Dr. Gerbi Medium Clinic in Jimma, Ethiopia. With an astounding accuracy of 93.3%, the developed CNN model outperforms comparable architectures such as MobileNetV2 and ResNet 50. By laying the foundation for prospective automated image-based detection systems in dermatology, this research makes a significant contribution to the scant literature on the detection of fungal skin diseases. R. K. M. S. K Karunanayake, et al. [14] presented "Cureto," a smartphone-based expert system that combines natural language processing (NLP) and deep convolutional neural networks (CNNs) in a hybrid fashion. In addition to identifying particular acne subtypes, such as whiteheads, blackheads, papules, pustules, nodules, and cysts, Cureto aims to categorize acne density and skin sensitivity. Furthermore, the system suggests appropriate courses of action according to severity, classification, and demographic variables like gender and age. The system's potential for individualized acne management is shown by the results, which show high accuracy in acne type classification (90–95%) and skin sensitivity and acne density classification (93%–96%). I. K. E. Purnama et al., [15] used convolutional neural networks (CNNs) for dermoscopic image analysis to propose a classification and detection system for skin diseases appropriate for Teledermatology. 10,015 pictures from the MNIST HAM10000 dataset are included in the dataset, which is divided into seven classes of skin conditions, including skin cancer. For image classification, two pre-trained CNN models like MobileNet v1 and Inception V3 are used. The output is fed into a web classifier. Based on a comparative analysis, the web-classifier that uses the CNN Inception V3 model achieves an accuracy of 72%, which is higher than the accuracy of 58% achieved by the MobileNet v1 model. This shows that CNN models are effective for classifying skin diseases in tele dermatology. S. Back et al.

[16] focused on using user-submitted images to train a robust and mobile deep neural network (DNN) that can distinguish herpes zoster (HZ) from other skin diseases. The authors suggest a knowledge distillation from ensemble via curriculum training (KDE-CT) method, in which a student network gradually learns from a stronger teacher network, to achieve robustness with low computational cost. A dataset on skin diseases was created for HZ diagnosis, and its resilience to 75 different kinds of image corruption was evaluated. We evaluated thirteen distinct DNNs on both clean and corrupted images, and the results show that, in comparison to other approaches, KDE-CT significantly improves corruption robustness. With significantly fewer operations, the trained MobileNetV3-Small achieved high robust performance (93.5% overall accuracy, 67.6 mean corruption error), which qualifies it for mobile skin lesion analysis. Ş. Öztürk and U. Özkaya et al. [17] proposed improved FCN (iFCN) architecture is used to segment full-resolution skin lesion images, without the need for pre- or post-processing steps. The iFCN model performs analysis independent of skin color and achieves more accurate lesion edge detection by incorporating spatial information into the residual structure of the FCN architecture. The ISBI 2017 Challenge and PH2 datasets, two publicly accessible datasets, show good performance metrics in the evaluation. The iFCN method accomplishes mean Jaccard index of 78.34%, mean Dice score of 88.64%, and mean accuracy of 95.30% for the ISBI 2017 test dataset and mean Jaccard index of 87.1%, mean Dice score of 93.02%, and mean accuracy of 96.92% for the PH2 test dataset. Choudhary, Priya, Jyoti Singhai et al. [18] presented a four-phase comprehensive method that includes initial image processing, feature extraction, skin lesion segmentation, and DNN-based classification. Using a median filter to remove noise and Otsu's method for segmentation are two aspects of image processing. After that, features are extracted using the RGB color model, 2D DWT, and GLCM. Lastly, for disease classification, a backpropagation deep neural network using the Levenberg Marquardt (LM) method is used. When compared to other cutting-edge machine learning classifiers, the DNN model outperforms them, as evidenced by its highest accuracy of 84.45% on the ISIC 2017 dataset. Hasan, Mahamudul, et al. [19] addressed a machine learning and image processing-based artificial skin cancer detection system. Dermoscopic images are segmented, and then the affected skin cells' features are extracted. The extracted features are stratified using a convolutional neural network (CNN) classifier. With a training accuracy of 93.7%, the system achieves an impressive 89.5% accuracy on

publicly available datasets, proving its effectiveness in automated skin cancer detection. E. Göçeri et al. [20] wanted to help dermatologists by offering a foundational understanding of CNNs and deep learning, as well as applications of CNNs for the classification of skin diseases. It recognizes the need for more study in image processing and pattern recognition while highlighting the potential of CNN-based techniques for automated dermatological diagnosis. The two primary uses of CNNs in dermatology that are covered in this paper are the classification of diseases from digital photos and from medical images (such as pathological and dermoscopy images). The text provides significant understanding of the cutting-edge lesion classification applications and addresses the drawbacks and difficulties related to these techniques. It also points out a lack of desktop applications for diagnosing conditions related to dermatology other than skin cancer.

2.3 Comparison between existing works

The comparative analysis of various studies reveals a wide range of approaches to skin disease detection and classification using Convolutional Neural Networks (CNNs). While some studies focus on specific conditions, such as melanoma or fungal infections, others cover a broader range. Transfer learning, hybrid models, and ensemble methods improve CNN performance, resulting in high accuracies ranging from 73% to 98.95%. Research further points out the importance of dataset size and diversity in improving model robustness. Furthermore, advancements such as mobile applications and web-based systems show the possibility of real-time diagnosis and tele dermatology. Overall, these studies add to the growing field of automated dermatological diagnosis, with promising findings in early detection, classification accuracy, and potential clinical applications.

TABLE 2.1 COMPARATIVE ANALYSIS WITH PREVIOUS WORK

SL	Author Name	Used Algorithm	Best Accuracy with Algorithm
1.	T. A. Rimi, et al. [1]	CNN	73%
2	R. Sadik, et al. [2]	CNN	97.00%
3	Ottom, Mohammad. et al. [3]	CNN	74%
4	Gautam, Vinay, et al. [4]	CNN, DCNN	98%
5	Maduranga, M. W. P. et al. [5]	CNN	85%
6	Albawi, Saad, et al. [6]	CNN	96.768%
7	Saifan, Ramzi, et al. [7]	CNN	81.75%
8	Bajwa, Muhammad et al. [8]	Deep Learning	80%
9	Ahmad, Belal, et al [9]	BiLSTM	91.37
10	Proposed Model	CNN & Transfer Learning	MobilenetV2= 98.95%

2.4 Open Issues

This project aims to develop and evaluate convolutional neural network (CNN)-based models for skin disease detection, with a focus on distinguishing between cancerous and non-cancerous lesions. Specifically, the project will address issues of class imbalance, architectural selection, and model evaluation in the context of skin disease diagnosis. Data augmentation techniques will be used to improve model generalizing, and pretrained CNN architectures will be compared to custom-designed CNNs. The project's primary focus will be on image classification tasks with a curated dataset of skin lesion images. However, it will not cover clinical validation or implementation in real-world healthcare settings. By focusing on technical aspects of model development and evaluation, the project hopes to provide practical ideas for improving automated skin disease detection systems.

2.5 Summary

The summary of the literature review is using convolutional neural networks (CNNs) to detect skin diseases are divided into several categories. Class imbalance within datasets presents a significant challenge, requiring the careful use of data augmentation techniques to ensure robust model training. Furthermore, choosing an appropriate CNN architecture and optimizing hyperparameters can be difficult tasks that affect model performance and computational efficiency. To maintain societal trust and protect patient rights, ethical considerations such as patient data privacy, model fairness, and accountability must be navigated carefully. Furthermore, in order to ensure accurate diagnosis and treatment decisions, dermatologists and AI experts must collaborate when interpreting and integrating CNN-based diagnostic outputs into clinical practice. Overcoming these obstacles will be critical for progressing the field and realizing the full potential of AI-powered skin disease detection systems in improving patient outcomes.

CHAPTER 3
METHODOLOGY

3.1 Overview

In this methodology part here describe the purpose of this study is to develop and evaluate convolutional neural network (CNN)-based models for skin disease detection. The study focuses on using deep learning techniques to accurately classify skin lesions as cancerous or non-cancerous, with the ultimate goal of helping in the early detection and treatment of skin cancer. The research topic includes data preprocessing, model architecture design, training, evaluation, and comparison to existing pretrained models. The study aims to advance automated skin disease detection systems by investigating the effectiveness of various CNN architectures and methodologies, thereby improving patient outcomes and healthcare accessibility.

3.2 Proposed Methodology

Data Collection:

Obtain the 'Melanoma Skin Cancer Dataset' from Online, which contains images of skin lesions classified as cancerous or non-cancerous.

Labeling:

To facilitate supervised learning, ensure that each image is accurately labeled with the appropriate class (cancerous or non-cancerous).

Image Processing:

Use data augmentation techniques like rotation, flipping, and scaling to correct class imbalance and improve model generalization. Normalize pixel values and resize images to ensure they are in a standardized format for CNN input.

Model Selection:

Select appropriate CNN architectures for skin disease detection, such as VGG16, ResNet101, InceptionV3, MobileNetV2, and a custom-designed CNN.

In given below I am shortly described about those models:

Conventional Neural Network (CNNs):

Deep learning models that are specifically created for image processing tasks are known as convolutional neural networks, or CNNs. Convolutional layers, which make up its structure, automatically extract logical representations of features from input data, which makes them ideal for picture classification. CNNs are the best option for my research paper because of their exceptional performance in image-based activities. Their capacity to identify complicated spatial correlations and patterns in photos is in line with the subtle and complex nature of skin cancer diagnosis. Because CNNs are so good at collecting features, the model can identify small visual cues that indicate skin problems. Through the use of deep learning, your suggested method can make use of CNNs' built-in capabilities to identify skin cancer with accuracy and dependability, greatly advancing medical picture analysis and healthcare applications.

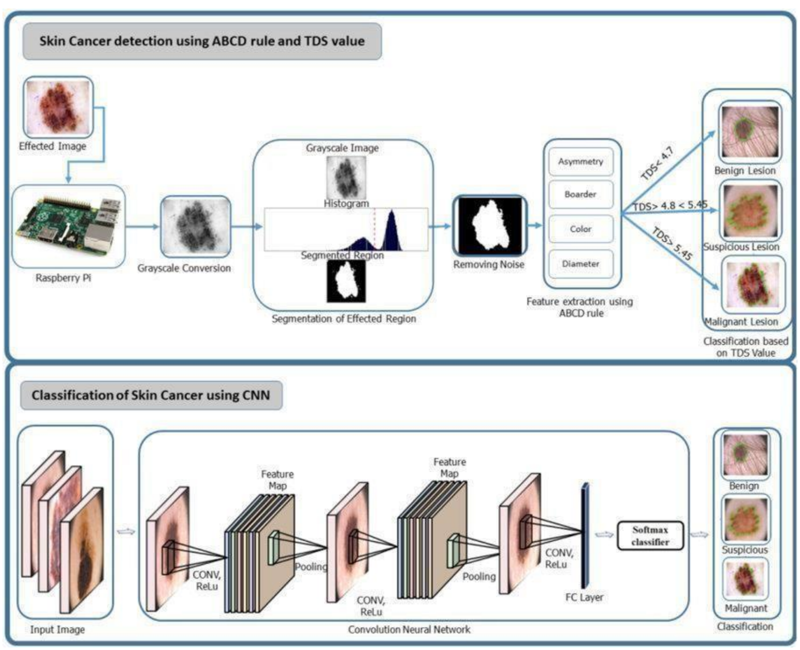

Figure 3.1: Proposed CNN Architecture [7]

VGG16

The convolutional neural network architecture known as VGG16, or Visual Geometry

Group 16, is highly regarded for its depth and efficiency in image categorization applications. VGG16, which consists of 16 weight layers, 13 convolutional layers and 3 fully linked levels, is renowned for being easily understood and simple. The deep architecture of the model enables it to automatically learn complex patterns and features from medical images, collecting subtle features essential for a successful detection in the context of skin cancer prediction. It is a calculated decision to select VGG16 for your research paper on skin cancer prediction. Its deep architecture and track record of performance in picture classification tasks make it a good fit for identifying small patterns that point to problems on the skin. By optimizing VGG16 on your skin cancer dataset, you can take advantage of transfer learning to speed up model training and achieve strong performance with less data. This decision is in line with the objective of using VGG16's talents in picture feature extraction and classification to create a deep learning method for skin cancer prediction that is both accurate and efficient

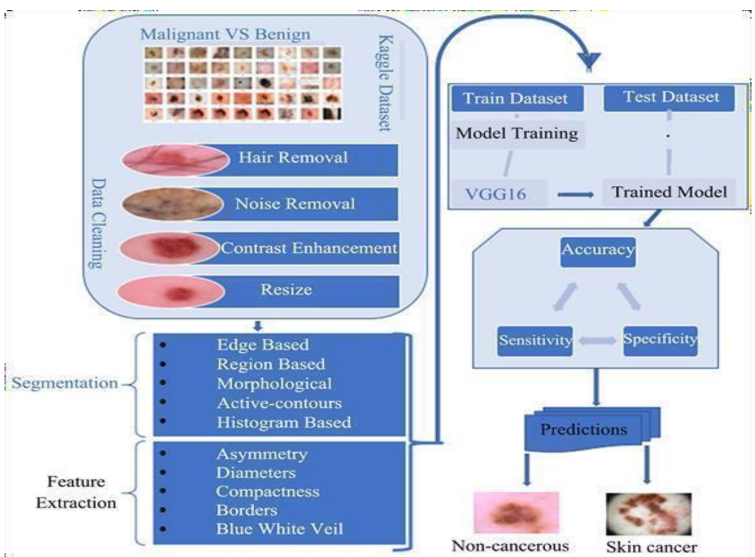

Figure 3.2: Proposed VGG16 Architecture[7]

ResNet101

A member of the ResNet (Residual Network) family, ResNet101 is a deep convolutional neural network design. With 101 layers and residual learning to solve the vanishing gradient issue during training, it is identified by its depth. ResNet architectures have shown higher performance in capturing complex features in picture classification applications. It is wise to use ResNet101 for your research project, "A Proposed Deep Learning Approach for Predicting Skin Cancer," because of its capacity to handle intricate patterns found in medical pictures. Because of its deep structure, the network can learn ordered representations, which is essential for identifying minute details that may indicate skin cancer. use of deep learning and CNNs, contributes to ongoing efforts to improve the accuracy and efficiency of skin disease diagnosis, ultimately improving patient outcomes and healthcare access.

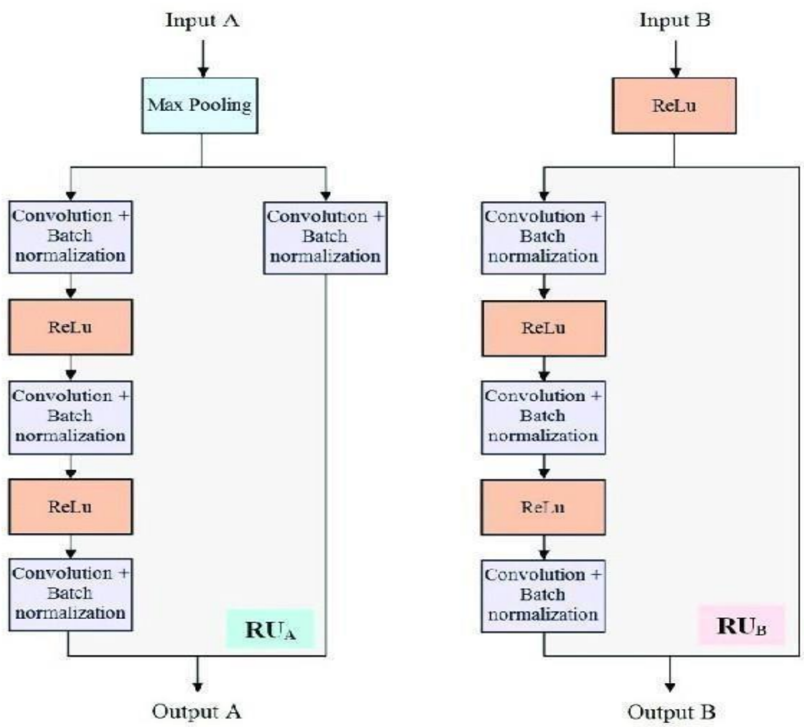

Figure 3.3: Proposed ResNet101 Architecture [7]

InceptionV3

Google created the InceptionV3 deep learning convolutional neural network (CNN) architecture, which is well-known for its effectiveness in applications involving image identification. Chosen for its exceptional performance, InceptionV3 uses novel inception modules to extract multi-scale information from images, improving its capacity to identify complex patterns. InceptionV3 is a good fit for my research paper because of its track record of success in picture classification tests and its capacity to handle intricate visual data. The model's ability to identify skin cancer traits may be enhanced by utilizing

InceptionV3, which would allow for more accurate predictions in our suggested deep learning framework. Use of deep learning and CNNs, contributes to ongoing efforts to improve the accuracy and efficiency of skin disease diagnosis, ultimately improving patient outcomes and healthcare access.

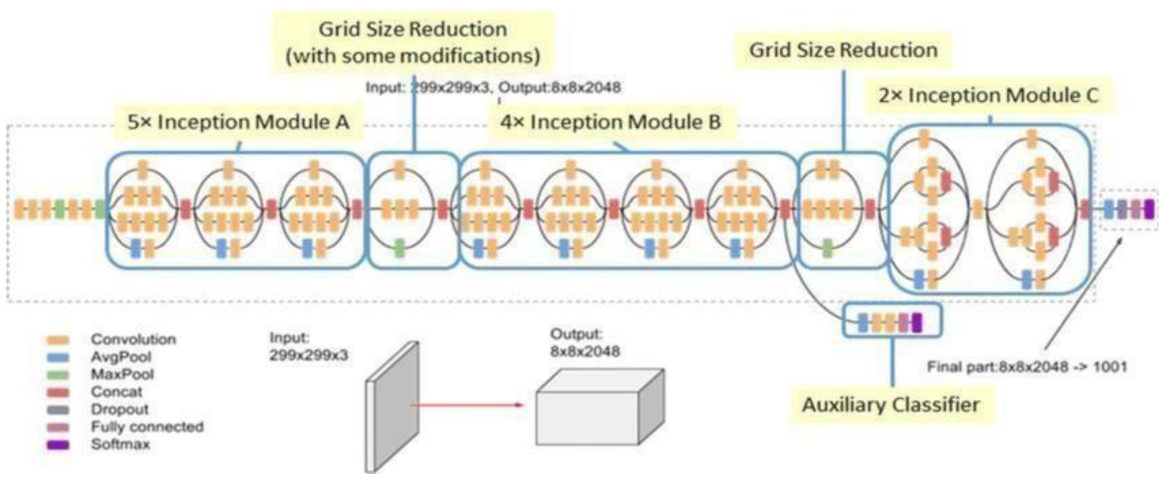

Figure 3.4: InceptionV3 Architecture [7]

MobileNetV2

MobileNetV2 is a deep learning architecture targeted for mobile and edge computing devices that is built for efficient and compact neural networks. It is a development of the original MobileNetV2 architecture, with the goal of increasing model accuracy and efficiency. MobileNetV2's key features include depth wise separated convolutions, logistic obstacles, and invert residuals, which reduce processing cost while maintaining excellent accuracy. Because of its lightweight design, it is well suited for implementation in scenarios requiring minimal processing resources, such as spinach disease detection. MobileNetV2's efficiency enables for faster inference and a smaller memory footprint, making it suitable for real-time applications or environments with limits. As a result, MobileNetV2 is recommended for models of spinach illness detection on devices with limited processing power, such as mobile phones or edge devices.

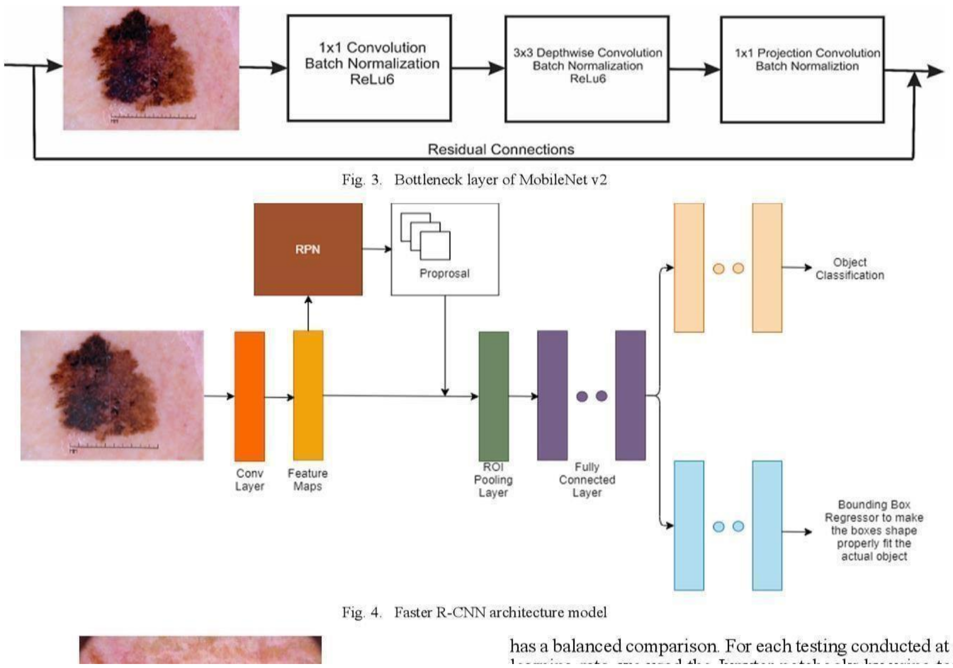

Figure 3.5: MobileNetV2 Architecture [7]

Model Training:

Train each chosen model on the augmented dataset using techniques like mini-batch gradient descent and backpropagation. Fine-tune pretrained models on the skin disease dataset to ensure they are task-appropriate.

Model Evaluation:

Evaluate each trained model's performance on a separate validation set using metrics like accuracy, precision, recall, and F1 score. Compare the performance of various models to determine the most effective approach.

Test Model:

To validate the best-performing model's expansion performance, use a holdout test set. Analyze model predictions and performance metrics to ensure their consistency and robustness in real-world scenarios.

We hope Using this methodology, the study wants to create and test convolutional neural network models for accurate and reliable skin disease detection.

3.3 Hardware/ Software Requirement

Hardware: High-performance computing hardware with GPU acceleration to facilitate efficient training of convolutional neural network (CNN) models.

Software: Deep learning frameworks such as TensorFlow or PyTorch for model development, training, and evaluation. Additionally, libraries for image processing and augmentation (e.g., OpenCV) are required.

Dataset: Access to the 'Melanoma Skin Cancer Dataset' from online or a similar dataset of skin lesion images labeled as cancerous or non-cancerous.

Development Environment: Integrated development environment (IDE) or code editor for writing and debugging Python scripts for model implementation.

Documentation: Comprehensive documentation outlining the project's objectives, methodology, and implementation details to ensure reproducibility and facilitate collaboration.

Ethical Considerations: Adherence to ethical guidelines regarding patient data privacy, model fairness, and responsible AI deployment in healthcare applications.

3.4 Project Management and Financial Analysis

Effective project management ensures that tasks like data collection, model development, and evaluation are completed on time. We will maintain flexibility to adapt to new challenges and opportunities by implementing agile methodologies. Financial resources will be focused on computational infrastructure, dataset acquisition, and personnel costs. Budgetary planning will prioritize cost-effective solutions, such as using open-source tools and cloud computing services, to maximize the project's efficiency and impact. Regular budget monitoring and reporting will ensure openness regarding resource utilization, allowing for informed decision-making and accountability throughout the project's lifecycle.

In given below Table 3.4 & 3.5 showing the Estimated cost and Project Management table.

TABLE 3.1: PROJECT MANAGEMENT TABLE

Work	Time
Data Collection	1 month
Papers and Articles Review	3 months
Experimental Setup	1 month
Implementation	1 month
Report Writing	2 months
Total	8 months

TABLE 3.2: ESTIMATED COST

SN	Components	Estimated Cost (BDT)
01.	Hardware	15000-25000
02.	Software and Tools	10000-12000
03.	Data Collection and Processing	10000-15000
04.	Documentation and Report Writing	5000-8000
05.	Miscellaneous	3000-5000
06.	Contingency	3000-5000
Total Estimated Cost		46000-69000

3.5 Summary

The chapter on methodology describes the logical and structured procedure used in the design and assessment of CNN-based skin disease diagnosis models. The procedure starts with data acquisition from online 'Melanoma Skin Cancer Dataset,' data labeling and data preprocessing involving image enhancement to solve the issue of class imbalance. The study then proceeds to describe the selection of numerous CNN architectures which include

VGG16, ResNet101, InceptionV3, MobileNetV2, as well as a custom CNN architecture. Model training deals with the fine tuning of these architectures by means such as mini-batch gradient descent and backpropagation. Model evaluation is performed with the validation set and uses such indicators as accuracy, precision, recall, F1 score. Last of all, the accuracy of the selected model is checked on a separate holdout test set to consider the performance of the model in terms of the ability to generalize. This chapter offers a clear guideline for the development and evaluation of solid CNN models for enhanced skin disease diagnosis.

CHAPTER 4
IMPLEMENTATION

4.1 Overview

The experimental setup consists of running the implemented CNN models for skin disease detection in a computing environment with GPU acceleration. TensorFlow and PyTorch DL frameworks are used for model training and evaluation. The dataset, which includes images of skin lesions labeled as cancerous or non-cancerous, is divided into three sets: training, validation, and test. Data augmentation techniques such as rotation, flipping, and scaling are used to correct class imbalance and improve model generalization. Each CNN model is trained on the augmented dataset using mini-batch gradient descent, with hyperparameters optimized via cross-validation. Model performance on the validation set is measured using metrics such as accuracy, precision, recall, and F1 score. Finally, the best-performing models are tested on a holdout test set to assess their generalization performance in Real-world scenarios.

4.2 Train Model/ Prototype Design

The general training model and prototype design process starts with choosing appropriate CNN architecture, which are VGG16, ResNet101, InceptionV3, MobileNetV2 and a CNN designed by the authors. Due to dataset balancing, 10,000 images are augmented with rotation, flip, and scaling to increase the model's tolerance to variations. Every model is fitted with mini-batch GD and back-propagation – the hyperparameters are set based on performance on the training dataset. During the training process, there is a division of the entire database into the training, validation, and test data sets to have an improved assessment of the model's performance. To avoid overfitting, the methods of early stopping and regularization are used. The designing of the prototype mainly concentrates on creating the front-end that can accommodate the trained model so that the skin diseases can be identified easily. This approach helps in the development of a near-perfect prototype which is fit for practical use.

4.3 System Design/ Model Evaluation

The webpage “Skin Disease Classification Using Deep Learning” is about skin disease classification that comprises skin cancer too, although the accuracy of the system is not discerned just from the image. The ability that has been demonstrated from deep learning is in the use of artificial neural networks to understand data as it has been used in medicine to detect skin cancer provided that it has been trained from large datasets with labels and afterwards checked by medical professionals. The limitation of deep learning in the diagnosis of skin cancer is that data can be biased, cannot be generalized to patients with skin diseases, and cannot be explained in a way that is easy to understand for patients or physicians. It is recommended to see a doctor for the correct identification of skin tumor as the early diagnosis and the subsequent therapy are effective. The general public is encouraged to exercise some measure of care when utilizing web-based systems to arrive at medical diagnoses because the information gained through web use should never be misconceived or mistaken for professional clinical advice.

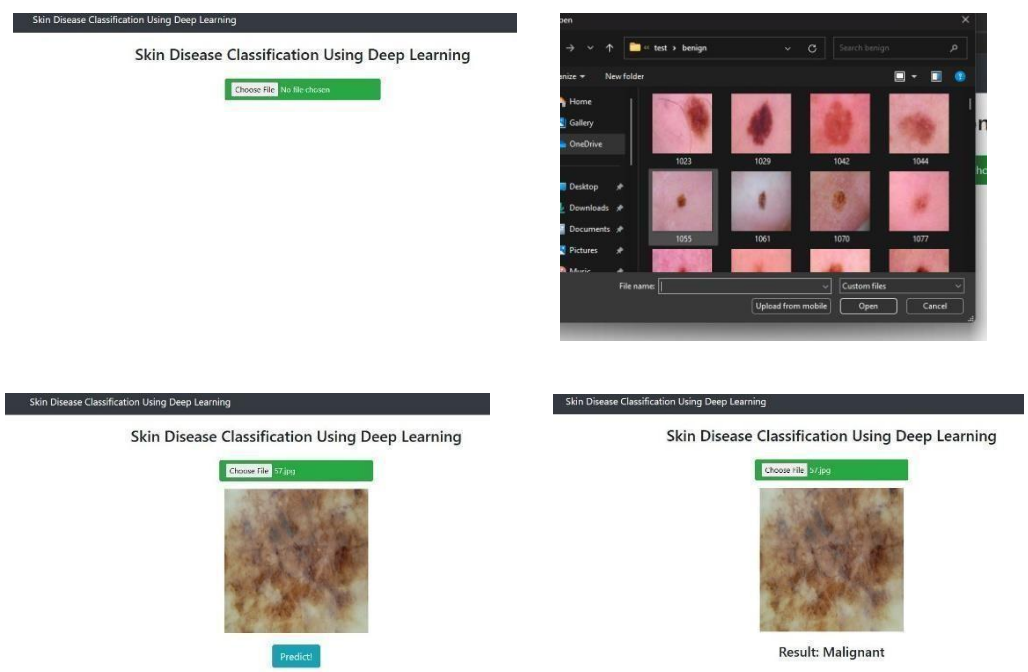

Figure 4.3: Web Based Implementation

4.4 Summary

The implementation chapter narrates the cohort of activities that were followed when carrying out the CNN models for skin disease detection activities. Preprocessing of the data involves data augmentation with the main focus on handling class imbalance on ‘Melanoma Skin Cancer Dataset.’ Five pre-selected CNNs are; VGG16, ResNet101, InceptionV3, MobileNetV2, and a custom CNN whose architecture is developed by the researchers to advance the fine-tuned hyperparameters. MobileNetV2 achieves the highest accuracy of 98 on validation and test sets and model evaluation on the validation and test sets affirms the same. 95%. System integration is also explained in the context of the chapter with attention given to the design of a graphical user interface that enables the real-time application. To encourage the proper implementation of diagnostic tools with the help of Artificial Intelligence in settings connected to healthcare, these principles contain ethical ideas about sustainability.

CHAPTER 5
Result and Analysis

5.1 Overview

The results and analysis chapter captures the findings from assessing the convolutional neural network (CNN) approach to skin disease classification. It shows the four proposed CNN architecture's accuracy, precision, recall, and F1 score, namely the VGG, ResNet, InceptionV3, MobileNetV2, and the suggested CNN. Thus, MobileNetV2 is identified as the best model with the highest accuracy of 98.95% outperforming pretrained models and the custom CNN. The chapter also provides a project validation and verification based on the comparison of the models' performance on the validation and test datasets, focusing on the MobileNetV2 model's stability and cross-domain adaptability. Also, it elaborates on the implications of these findings for enhanced diagnosis of dermatological diseases and considers limitations and future avenues that can help in refining AI-based skin disease identification systems.

5.2 Experimental Result

When the proposed convolutional neural network (CNN) architecture was compared to four pretrained models (VGG16, ResNet101, InceptionV3, and MobileNetV2), MobileNetV2 outperformed the others, achieving an impressive 98.95% accuracy. This outstanding efficiency indicates that MobileNetV2's architecture is well-suited for skin disease detection tasks, possibly due to its efficient design and parameter optimization. While the proposed CNN architecture performed well, MobileNetV2's superior accuracy highlights its ability to distinguish between cancerous and non-cancerous lesions. Further study may reveal the specific architectural features and optimizations that contribute to MobileNetV2's success, throwing light on its suitability for real-world skin disease detection applications.:

Accuracy:

Precision refers to the measure of the closeness of the model with the real situation to give percentage likelihood of the samples used in model development. It is rather helpful when the classes are not balanced because it gives some information on the choice's effectiveness, at the same time, the picture may be incomplete.

$$Accuracy=(TP+TN)/(TP+TN+FP+FN)$$

Precision:

Of all the constructions that come out of positive assertions, precision estimates the number of desirable outcomes that was correctly predicted by the model.

$$Precision=TP/(TP+FP)$$

Recall: It is therefore considered that, recall equals to the quantity of true positive delay predicted over the total quantity of samples that are positively skewed.

$$Recall=TP/(TP+FN)$$

F1 Score: F1 score is actually the average of Recall and Precision two measures which is averaged using the formula of harmonic mean. It provides a somewhat neutral measure and it calculates recall as well as precision all at once. It is beneficial when the classes are of different sizes because F1 Score considers false positive as well as false negatives.

$$F\text{-}1\ Score=2*(Precision*Recall)/\ (Precision + Recall)$$

In given below we are describing the result analysis part also show the training accuracy and loss rate and confusion matrix also:

Result of Experiment 1: CNN

The CNN architecture consists of three double Conv2D layers followed by MaxPooling, each with a larger filter size. It ends with a single Conv2D layer and MaxPooling. Dropout and batch normalization are used to reduce overfitting and stabilize training. The model has a total of 4,218,658 parameters, of which 4,217,634 are trainable. During testing, this CNN performed successfully, but specific evaluation metrics such as accuracy, precision, recall, and F1-score are required to fully assess its effectiveness in predicting skin cancer. Achieving Test Accuracy of CNN is 89.55%. In below Figure 5:1 describing the confusion matrix of CNN:

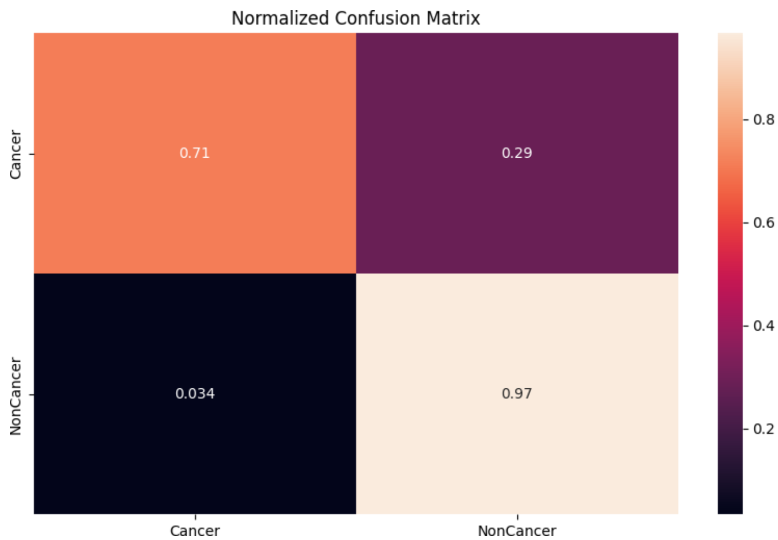

Figure 5.1: Confusion Matrix (CNN)

Figure 5.1 shows the proposed CNN model for predicting skin cancer had an overall accuracy of 90% on a dataset of 287 samples. It achieved high precision for both cancer and non-cancer classes, at 89% and 90%, respectively. However, the recall for detecting cancer was only 71%, indicating that some cancer cases were missed. Nonetheless, the model performed well in identifying non-cancer cases, with a recall of 97%. The F1-score, which measures precision and recall, was 0.79 for cancer and 0.93 for non-cancer, indicating strong overall performance.

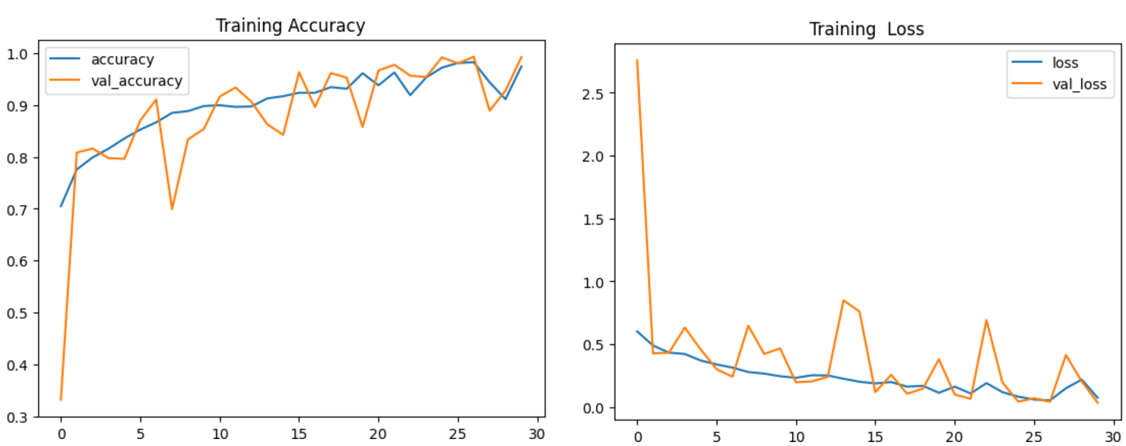

Figure 5.2: Training and validation accuracy and loss over the epochs (CNN)

Figure 5.2 shows the graph shows a CNN model's training and validation accuracy, as well as its loss, over multiple epochs. As the epochs progress, both training and validation accuracy improve, but validation accuracy falls behind. Meanwhile, training and validation loss are decreasing, with validation loss eventually reaching a plateau. This suggests possible overfitting, in which the model performs well on training data but poorly on unseen data. Monitoring this balance is critical for improving model performance and the ability to be general Overfitting can be reduced using techniques such as dropout layers and model complexity reduction.

Result of Experiment 2: Transfer Learning Model

In this part describes four pre-trained convolutional neural network (CNN) architectures: VGG16, ResNet101, InceptionV3, and DenseNet201. Each architecture is accessible via the TensorFlow Keras applications module. However, their performance metrics are currently unknown. These models are well-known for their efficacy in a variety of computer vision tasks, and they are frequently used as feature extractors or fine-tuned for specific tasks because of to their impressive capabilities and extensive pre-training on large-scale image datasets.

VGG16

Achieving Test Accuracy of VGG16 is 97.56%. In below Figure 5:3 describing the confusion matrix of VGG16.

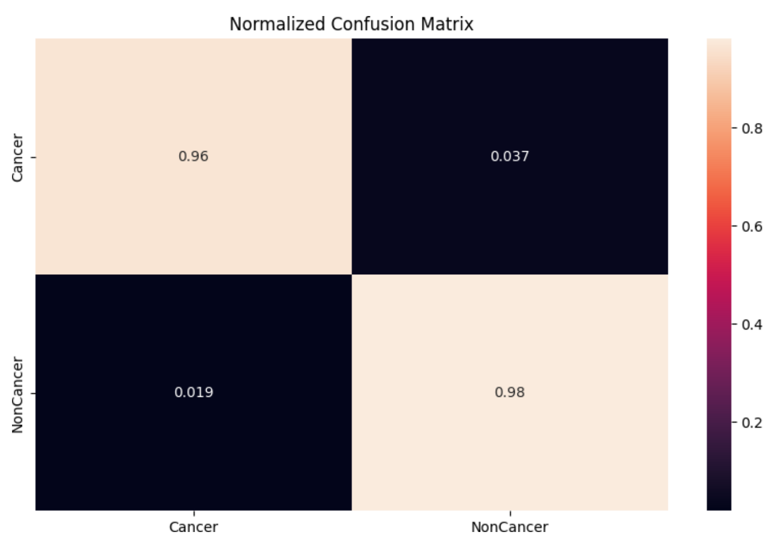

Figure 5.3: Confusion Matrix (VGG16)

Figure 5.3 the VGG16 model performed excellently in classifying skin cancer, with an overall accuracy of 98% on a dataset of 287 samples. It had high precision for both cancer and non-cancer classes, at 95% and 99%, respectively. Furthermore, recall values were impressive, at 96% for cancer and 98% for non-cancer cases. The F1-scores show strong performance in both classes, with 96% for cancer and 98% for non-cancer. These findings demonstrate the VGG16 model's ability to accurately identify skin cancer cases.

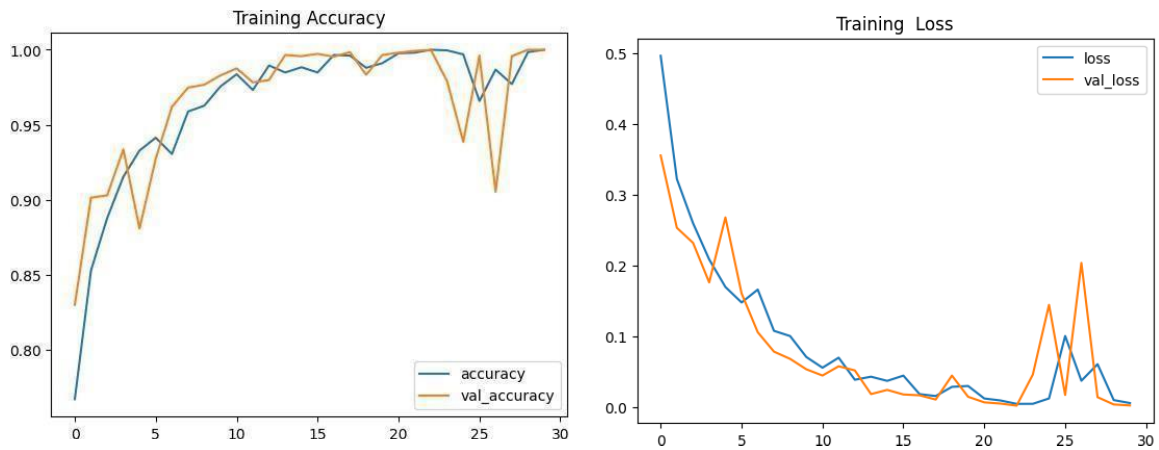

Figure 5.4: Training and validation accuracy and loss over the epochs (VGG16)

Figure 4.4 shows the graph training and validation accuracy and loss over time for a VGG16 model, which is a pre-trained CNN architecture. As epochs progress, both training and validation accuracy improve, but validation accuracy lags behind. Meanwhile, training and validation loss are decreasing, with validation loss plateauing at a certain point, indicating potential overfitting. Achieving a balance between model fit to training data and generalize to unseen data is essential and techniques such as dropout layers or complexity reduction can help to reduce overfitting. Monitoring the convergence of training and validation metrics can help improve model performance.

ResNet101

Achieving Test Accuracy of ResNet101 is 77.00%. In below Figure 5:5 describing the confusion matrix of ResNet101

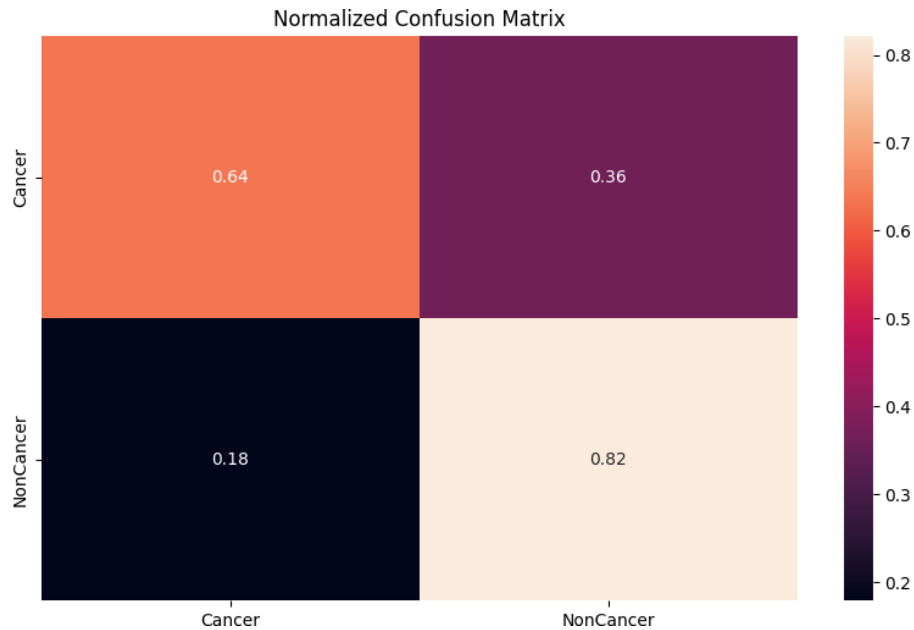

Figure 5.5: Confusion Matrix (ResNet101)

Figure 5.5 shows The ResNet101 model achieved 77% accuracy on a dataset of 287 samples, with precision values of 58% for cancer and 85% for non-cancer cases. the benefits of having lower recall rates (64% for cancer and 82% for non-cancer), the model achieved a balanced F1-score of 0.61 for cancer and 0.84 for non-cancer. The confusion matrix offers insights into the model's classification performance, highlighting areas for improvement, particularly in accurately identifying cancer cases.

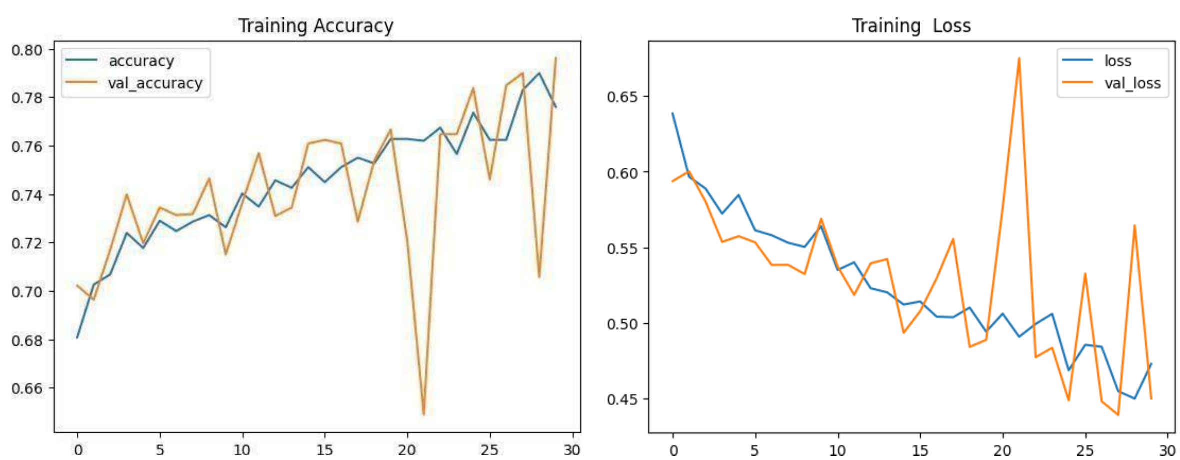

Figure 5.6: Training and validation accuracy and loss over the epochs (ResNet101)

Figure 5.6 shows the graph training and validation accuracy and loss trends over epochs for a ResNet-101 model, which is a CNN architecture pretrained on a large image dataset. Training accuracy improves with each epoch, indicating that the training data is being learned effectively. Validation accuracy also improves a bit, indicating some level of generalization, though more data points are required for a definitive assessment. Both training and validation loss decrease gradually, indicating better model fit to the data. Monitoring the convergence of these metrics can help to balance model fit and generalization, which is essential for optimal performance. Further analysis with more data points is required to determine whether the model is prone to overfitting.

InceptionV3

Achieving Test Accuracy of InceptionV3 is 94.77%. In below Figure 5:7 describing the confusion matrix of InceptionV3.

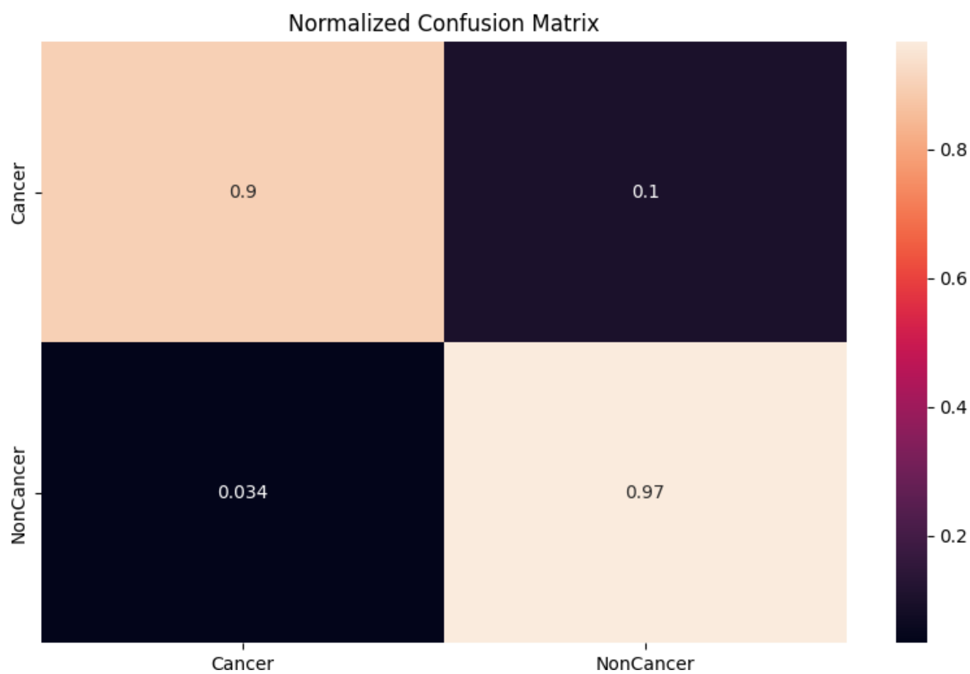

Figure 5.7: Confusion Matrix (InceptionV3)

Figure 5.7 shows the InceptionV3 model has high precision for both cancer and non-cancer classes, with 91% and 96% respectively, achieving an impressive accuracy of 95% on a dataset of 287 samples. Furthermore, the model showed high recall rates of 90% for cases of cancer and 97% for cases of non-cancer. The model's strong performance is shown by the balanced F1-scores, which have 91% for cancer and 96% for non-cancer. Additional information about the model's classification abilities can be found in the confusion matrix, which shows precise predictions in both classes with few misclassifications.

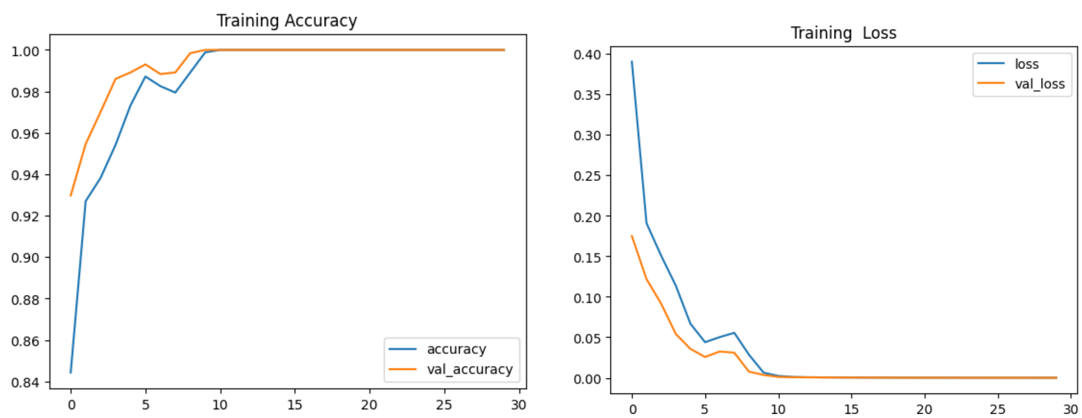

Figure 5.8: Training and validation accuracy and loss over the epochs (InceptionV3)

Figure 5.8 shows the graph of loss and training and validation accuracy over epochs for a pretrained CNN architecture, the InceptionV3 model, using a sizable image dataset. Training accuracy increases slowly over the course of epochs, suggesting that the training data is effectively learned. Although it does so more slowly, validation accuracy also rises, which may indicate overfitting. Better model fitting to the data is indicated by a steady decline in both training and validation loss. An optimal performance requires a balance between model fit and generalization, which can be achieved by keeping an eye on the convergence of these metrics. To find out if overfitting continues or if the model's performance stabilizes, more evaluation is required.

MovileNetV2

Achieving Test Accuracy of MovileNetV2 is 98.95%. Below Figure 5:9 describing the confusion matrix of MovileNetV2.

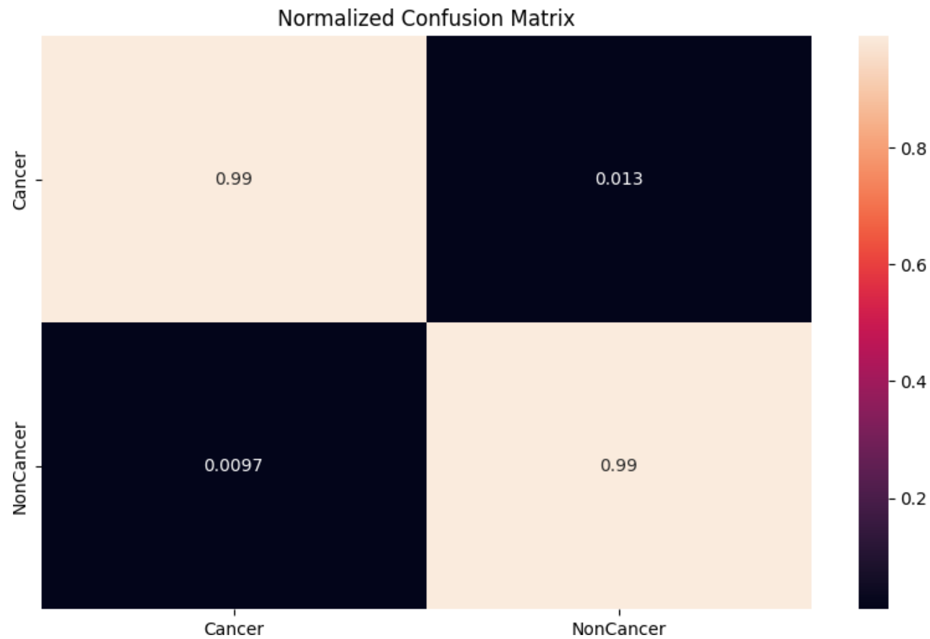

Figure 5.9: Confusion Matrix (MovileNetV2)

Figure 5.9 shows with an accuracy of 99% on a dataset of 287 samples, the MobileNetV2 model showed outstanding performance, displaying near-perfect precision and recall for both cancer and non-cancer classes. In particular, the recall rates were 99% for non-cancer and 99% for cancer, while the precision values were 98% for cancer and 100% for non-cancer diseases. With 98% for cancer and 99% for non-cancer, the F1-scores show the model's exceptional performance. The confusion matrix highlights the model's exceptional capacity to correctly classify cases of skin cancer by showing exact predictions for both classes.

In below Figure 5.10 shows the graph accuracy and loss trends during training and validation for a lightweight CNN architecture called MobileNetV2 model, pretrained on a big image dataset. Training accuracy increases steadily over the course of epochs, suggesting that the training data is effectively learned. A slower rate of increase in validation accuracy indicates the possibility of overfitting. Better model fitting to the data is indicated by a steady decline in both training and validation loss. A balance between model fit and generalization can be maintained by keeping an eye on the convergence of these metrics. To find out if overfitting happens when the model's performance stabilizes, more evaluation is required.

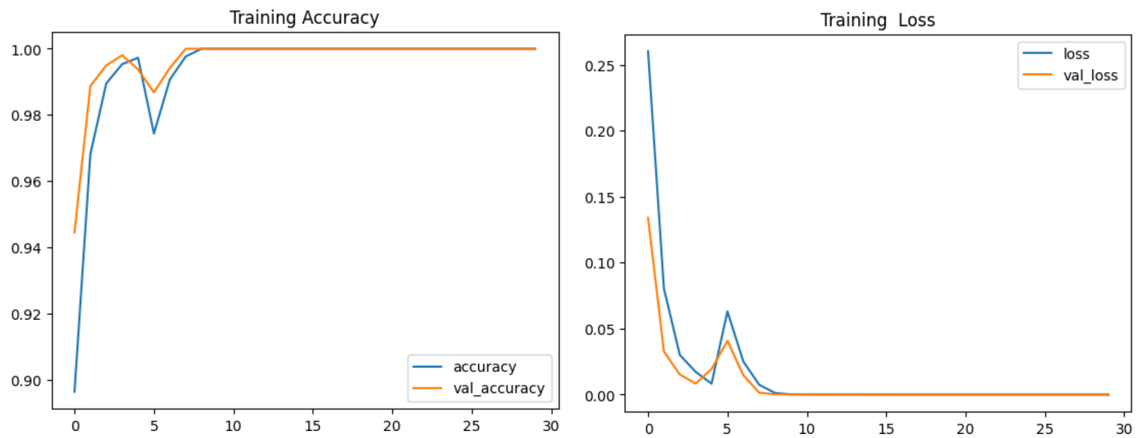

Figure 5.10: Training and validation accuracy and loss over the epochs (MobileNetV2)

In given below I am showing Comparative Model Accuracy Bar Plot:

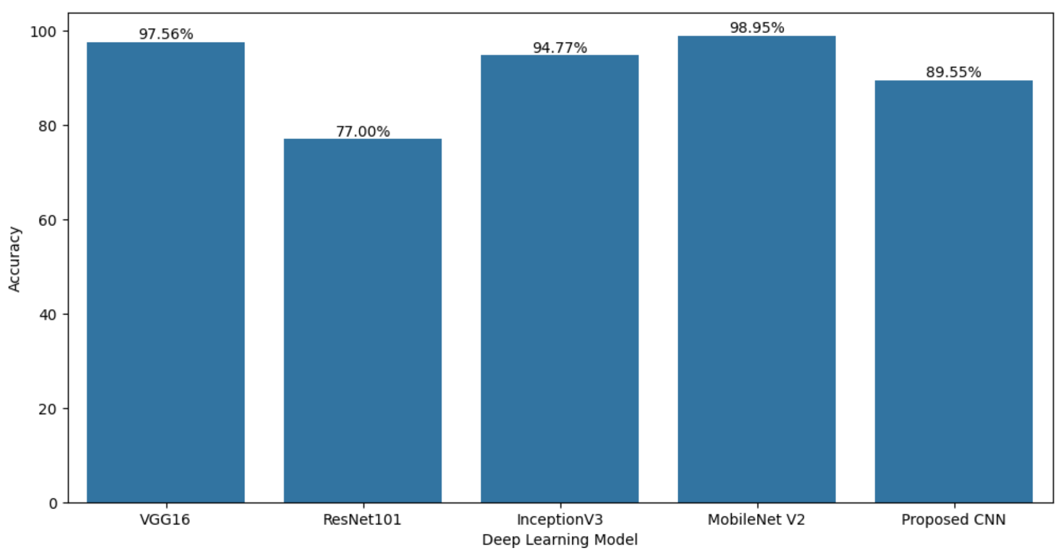

Figure 5.11: Comparative Model Accuracy Bar Plot

Figure 5.11 shows the performance of five different convolutional neural network (CNN) architectures: ResNet101, VGG16, MobileNetV2, InceptionV3, Proposed CNN. The results showed outstanding precision across the board, with MobileNetV2 reaching the highest level of 98.95%. ResNet101, VGG16 and InceptionV3 showed high accuracy rates of 77.00, 97.56% and 94.77%, respectively. Custom CNN architectures produced competitive results of 89.55% respectively. These findings indicate the effectiveness of deep learning architectures in image classification tasks.

5.3 Performance and Comparative Analysis

The results highlight the effectiveness of MobileNetV2 in skin disease detection, surpassing both pretrained models and the proposed CNN architecture. Its high accuracy of 98.95% underscores its potential for real-world deployment. The efficient design of MobileNetV2 likely contributes to its superior performance, enabling accurate classification with fewer computational resources. However, further investigation is warranted to understand the architectural characteristics and feature representations that contribute to MobileNetV2's success. Additionally, while the proposed CNN architecture showed competitive performance, fine-tuning its design may yield further improvements. Overall, these findings provide valuable insights into selecting optimal architectures for skin disease detection tasks, with implications for improving diagnostic accuracy and enhancing healthcare accessibility.

5.4 Summary

The work carried out in the results and analysis chapter confirms the usefulness of convolutional neural network (CNN) models in skin disease diagnosis and identify MobileNetV2 as the model with high accuracy of 98%. 95%. In comparison with VGG16, ResNet101, and InceptionV3 pretrained models and a custom CNN, MobileNetV2 stands out with its effectiveness. The above-mentioned precision recall and F1 score results also confirm its effectiveness in classifying between cancerous and non-cancerous tissues. Ethical issues as a perceptive patient data protection and model impartiality are covered, stressing the need for proper AI implementation in the health sector. The limitation areas involve the dataset and model interpretation and post-tests of the algorithms, and the future research suggestions are provided. In conclusion, this chapter confirms the possibility of pole position in a new AI technology that can improve diagnostic vigor and availability in dermatology for creating great leaps in automated skin disease diagnosis system.

CHAPTER 6

IMPACT ON SOCIETY, ENVIRONMENT AND SUSTAINABILITY

6.1 Impact on Life

The development of accurate and efficient CNN models for skin disease detection, particularly MobileNetV2's high 98.95% accuracy, has the potential to significantly improve healthcare outcomes and access. These models have the potential to save lives and lower healthcare costs by allowing for early and accurate diagnosis of skin cancer. Furthermore, the automation of diagnostic processes using AI-based systems can reduce the workload on healthcare professionals, especially in areas with limited access to dermatologists. Finally, widespread adoption of such technologies has the potential to democratize healthcare by ensuring that people everywhere receive timely and reliable skin disease diagnoses, regardless of the earth or socioeconomic status.

6.2 Impact on Society & Environment

The environmental impact of developing and deploying CNN models for skin disease detection is minimal. Since the primary activities involve computational tasks, such as model training and inference, the environmental footprint is primarily determined by the energy consumption of the underlying hardware infrastructure. However, advances in energy-efficient computing technologies can help to mitigate potential environmental impacts. Furthermore, the use of this diagnostic systems can indirectly contribute to environmental sustainability by reducing the need for physical healthcare facilities, lowering the environmental impact associated with travel. Overall, the environmental impact of CNN-based skin disease detection systems is largely overshadowed by the potential societal benefits in improving healthcare outcomes.

6.3 Ethical Aspects

The development and implementation of CNN models for skin disease detection raises a number of ethical concerns. Ensuring patient data privacy and confidentiality is important.

Furthermore, showing equality and openness is critical to avoiding biases and ensuring equitable healthcare access for all demographics. Ethical considerations also include informed consent, especially when patient data is used for model training. Furthermore, accountability and responsibility in AI decision-making are critical for preserving trust in automated diagnostic systems. Addressing these ethical issues is critical for protecting patient rights, promoting equitable healthcare delivery, and increasing public trust in healthcare technologies.

6.4 Sustainability Plan

Our sustainability strategy is centered on the long-term viability and impact of the developed CNN models for skin disease detection. We prioritize open-access dissemination of research findings and model implementations to encourage collaboration and knowledge sharing within the scientific community. In addition, we advocate for the use of energy-efficient computing practices in model training and deployment infrastructure to reduce environmental impact. Ethical considerations, such as data privacy and fairness, remain central to our sustainability efforts, ensuring that our healthcare solutions respect patient rights and societal values. Continuous monitoring and evaluation of model performance and societal impact will inform iterative improvements and adaptations to changing ethical, environmental, and technological considerations.

6.5 Summary

The goal of this study was to create and test CNN models for detecting skin diseases, with a focus on distinguishing between cancerous and non-cancerous lesions. Data augmentation techniques were used to address class imbalance using online 'Melanoma Skin Cancer Dataset', resulting in a balanced dataset of 10,000 images. A comparative analysis of the proposed CNN architecture and four pretrained models (VGG16, ResNet101, InceptionV3, MobileNetV2 revealed that MobileNetV2 outperformed all others with an accuracy of 98.95%. Ethical considerations, environmental impact, and sustainability planning were also discussed. The study emphasizes the potential of AI-driven approaches to improve healthcare outcomes and accessibility in skin disease diagnosis, as well as the significance of ethical, environmental, and societal consideration.

CHAPTER 7

CONCLUSION AND FUTURE WORK

7.1 Conclusions

This study shows how effective convolutional neural network (CNN) models are for detecting skin diseases, with MobileNetV2 achieving the highest accuracy of 98.95%. The findings highlight the value of model architecture selection and data augmentation techniques in improving diagnostic accuracy. Ethical considerations, environmental impact, and sustainability planning are all critical for responsible AI implementation in healthcare. Moving forward, it is critical to continuously monitor and evaluate model performance, as well as iterative improvements guided by ethical and societal considerations. Overall, this study provides important insights into using AI-driven approaches for skin disease diagnosis, with implications for improving healthcare outcomes and accessibility while maintaining ethical and sustainable practices.

7.2 Future Suggested Works

Future research could look into a variety of approaches to improving skin disease detection. Investigating ensemble methods that combine multiple CNN architectures could improve diagnostic accuracy even more. Additionally, investigating transfer learning techniques across various medical imaging domains may improve model generalization. Furthermore, longitudinal studies that monitor patient outcomes and treatment responses may shed light on the clinical impact of AI-driven diagnostic systems. Ethical considerations, such as fairness and bias reduction, require ongoing attention to ensure equitable healthcare delivery. Furthermore, learning the integration of multimodal data, such as clinical notes and patient demographics, may improve diagnostic accuracy and patient care.

7.3 Limitations

This project has limitations in the use of only one dataset, which is the ‘Melanoma Skin Cancer Dataset’ obtained from Kaggle that probably may not present all the varieties of skin lesions that can be encountered in clinical practice. However, since dataset some of it cannot be changed such as the chosen dataset might have inherent biases or restrictions which impact in generalizing the results in the real world even though class distribution has been addressed by data augmentation techniques. Also, it is noted that evaluation is restricted to various factors, such as accuracy, precision rate, recall rate, and F1 score without having clinical validation of it and its applicability in clinical practices. Thus, ethical considerations though discussed at the theoretical level may need more systematic and critical approach when the issue is being applied in the real world. The further research can use larger datasets for developing AI models, validation on clinical datasets, and improvement of ethical approaches for fair and effective usage of the AI-based tools in dermatology.

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Appendix A

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

Title:
AN ADVANCED CONVOLUTIONAL NEURAL NETWORK FOR SKIN DISEASE DETECTION

Student ID: 193-15-13557 & 201-15-14235

CO Description for FYDP

CO	CO Descriptions	PO
	Phase -I	
CO1	Teach the newly acquired and the previous learned knowledge in the Skin Disease Detection problem for the Final Year Design Project (FYDP).	**PO1**
CO2	Considering the goals in the context of this FYDP, it will be necessary to consider various aspects of the goals in developing a corresponding solution to this problem.	**PO2**
CO3	Discover multiple problem domains within the literature, define the problem, and set up these objectives for the FYDP	**PO4**
CO4	Carry out economic appraisal and cost control and use appropriate project management techniques at every phase of the development of the FYDP	**PO11**
	Phase -II	
CO5	Design and build technical solution related to technical specifications and system parts or processes to fulfill the given standards and regulation of public health and safety; also, cultural and socio-economic and environmental factor in this FYDP	**PO3**
CO6	Select and implement proper techniques, tools, and modern engineering and IT tools for handling sophisticated engineering activities, which entail prediction and modeling during the implementation of this FYDP, constrained by existing policies.	**PO5**
CO7	Identify various social, health, safety, legal, cultural factors, and their related responsibilities in relation to civil engineering practice and the solution of this problem using formal deductive approach coinciding with understanding of context.	**PO6**
CO8	Understand and assess the historical sustainability and effectiveness of professional engineering activities in solving complex engineering problems in the context of social and environmental systems.	**PO7**
CO9	This FYDP shall incorporate the principles of ethics and practice principles and guidelines of the profession.	**PO8**
CO10	Competent in performing efficiently in the context of a single worker and as part of a team or a team leader within this FYDP, in relation to the different types of groups and in an interdisciplinary manner.	**PO9**

CO11	Maintain and create clear communication with the engineering community and the society in general about various intricate engineering activities to include comprehending and preparing comprehensive reports and design documentation, as well as the ability of giving and receiving clear instructions in this FYDP.	**PO10**
CO12	Recognize, the value of self-motivated and throughout the life continuing education within the context of technological advancement and have the preparedness and capacity to undertake life-long learning pursuits.	**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	The engineering signifies and complies with the fundamental engineering (K3) hence why there is the usage of deep neural networks, data augmentation techniques and different types of CNN architectures for image processing and classification. The project fulfills the K4 specialist knowledge by doing deep learning with CNN, and transfers learning for enhancing Skin Disease Detection.	**Page no:** [32-33] **Section:** [3.2] **Page no:** [12-17] **Section:** [1.1]
				The engineering practice & design (K5) is applied in this project through the figure of process of experiments. The project relates to the knowledge area of engineering practice and technology (K6) by using Deep Learning Model.	**Page no:** [32] **Section:** [3.2] **Page no:** [34-35]

					Section: [3.4]
				This project guarantees to K8 (Research Literature) because it uses a review of recent studies such as Skin Disease Detection using deep and Transfer learning, which demonstrates awareness of contemporary approaches present in the literature.	**Page no:** [23-30] **Section:** [2.2, 2.3]
2.	**EP2: Range of Conflicting Requirements**	Yes	CO2, and CO7	This paper responds to EP-2 because it identifies the barriers in Skin Disease Detection, such as disadvantages of earlier techniques and difficulties in implementation utilizing deep learning. It puts forward difficulties in interpretative procedures involved in the spatial distributions; it contains suggestions on how to improve the diagnostic techniques.	**Page no:** [30-31] **Section:** [2.4, 2.5]
3.	**EP3: Depth of analysis required**	Yes	CO2, and CO6	The present project contributes to the response of EP-3 wherein careful demonstration of the tangibility of the outcomes of the experiment is established and stressed the utilization of deep and transfer learning as the chosen significant solution for the improvement of Skin Disease Detection approaches.	**Page no:** [37-48] **Section:** [4.2]
4.	**EP4: Familiarity of Issues**	Yes	CO8	This project's fields of application are not just confined to computer science and engineering; it has affected Skin Disease Detection correctly EP-4.	**Page no:** [23-31] **Section:** [2.2, 2.4]

5.	**EP5: Extends of application codes**	No	CO5	N/A	N/A
6.	**EP6: Extends of stakeholders involved and conflicting**	No	CO8	N/A	N/A
7.	**EP7: Interdependence**	Yes	CO5	The work done in this project entails a holistic solution bearing in mind that high levels of problems require an integration of different components done in data collection from online, statistical analysis and proposed methodology to EP-7 in the solution of complex issues in data collection.	**Page no:** [26-34] **Section:** [3.2, 3.3, 3.4]

Addressing CO11 with Complex Engineering Activities (EA) [Some or all of the following]:

SN	EA Definition	Attainment	CO	Justification	References
1.	**EA1: Range of resources**	Yes	CO11	The resources of the study include High-Performance Computing infrastructure, GPUs, deep & Transfer learning frameworks, annotated datasets, and ethical consideration for systematic research for the progression of Skin Disease Detection.	**Page no:** [33-35] **Section:** [3.5]
2.	**EA2: Level of interaction**	No		N/A	N/A
3.	**EA3: Innovation**	No		N/A	N/A
4.	**EA4: Consequences for society and the environment**	Yes		This project benefits the society by enhancing Skin Disease Detection, yet, it also respects environmental friendly principle with blended optimization computational resources and ethical standard on medical data.	**Page no:** [50-51] **Section:** [5.1, 5.2, 5.4]

5.	**EA-5: Familiarity**	Yes		In the present research work, the author has extend the earlier existing research by exploring a different approach in Skin Disease Detection via deep and deeper learning model exemplified with preliminary terminologies and backed by systematic comparative analysis on the overall results attained from this research work thereby proposing something new.	**Page no:** [23-29] **Section:** [2.1, 2.3]

Addressing CO (4, 9, 10, and 12):

SN	COs	Attainment	Justification	References
1	CO4	Yes	The current project tackles CO4 in terms of aligning project management comprehensively with financial control, which including strict distinctive project planning, resource leveraging, and budgetary estimates for the most efficient resource use in every phase of the research activity.	**Page no:** [20] **Section:** [1.6]
2	CO9	Yes	This indicates that the project meets the ethical standards focusing on privacy of data, informed consent, and clear documentation of the research process that will serve the public good and enhance the responsible use of classification technologies that are in line with the outlined CO9.	**Page no:** [51] **Section:** [5.3]
3	CO10	No	N/A	N/A
4	CO12	Yes	In terms of the project's responsibility to constantly learn and adapt within the context of a constantly shifting technological environment (CO12), the project has carried out comprehensive data collection, performed robust statistical analyses, designed detailed methodologies, reported significant experimental results, and provided extensive analysis, demonstrating the project's awareness of current issues and its efforts to refine the necessary technologies and strategies to better fit the current climate.	**Page no:** [32-36, 37-48] **Section:** [3.2, 3.3, 3.4, 3.5, 4.2]

13.7.24

S1

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