A Robust Shallow CNN Architecture for Performing Ablation Studies on Skin Cancer Images

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APPROVAL

This Project/internship titled **"A Robust Shallow CNN Architecture for Performing Ablation Studies on Skin Cancer Images"**, submitted by Md. Tanvir Hasan, ID No: 191-15-2463 and Md. Soriful Alam, ID No: 191-15-2408 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 01 February 2023.

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I hereby declare that, this project has been done by me under the supervision of **Mohammad Jahangir Alam, Senior Lecturer, Department of CSE,** Daffodil International University. I also declare that neither this project nor any part of this project has been submitted elsewhere for award of any degree or diploma.

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ABSTRACT

Skin disease is an increasingly common form of disease that affects millions of people worldwide every year. It is caused by the uncontrolled growth of abnormal skin cells. Skin disease detection is an important area of medical research as skin diseases can have a major impact on the quality of life of patients. As a result of a significant amount of data available for model training and improved model designs, Deep Learning techniques have grown rapidly for computer vision applications. This study aims to describe a robust deep-learning CNN model that categorizes skin disease using into six classes based on a deep learning-based CNN. The uninvited regions of skin disease are removed, the image is enhanced, and the disease is tinted by removing artefacts, reducing noise, and improving the image. The augmentation techniques have increased the number of skin disease images. Initially a base CNN model has been proposed in the augmented dataset. An ablation study has been employed to get the robust CNN model, which name is SkinNet-11. The model is trained with a set of publicly available skin disease images. The proposed robust SkinNet-11 achieved the best results with 98.00% accuracy. The model is robust and shows a high degree of generalizability on unseen data. The model also achieves a high level of precision and recall in both binary and multi-class skin disease detection scenarios.

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CHAPTER 1
Introduction

1.1 Introduction

Skin diseases are a major global health problem, affecting people of all ages, ethnicities, and socioeconomic backgrounds. They can range from mild, barely noticeable conditions to severe, life-threatening illnesses. In the world, one-third of all cancers are skin cancers, according to the World Health Organization (WHO) [1] [2]. There has been a steady increase in the incidence of this disorder over the past few decades around the world. In 2019, the American Cancer Society estimates that more than 5 million people will be diagnosed with skin cancer [3]. The mortality rate of skin diseases varies greatly depending on the type of skin disorder, the severity, and the patient's age, gender, and overall health. For example, the mortality rate for melanoma, a type of skin cancer, is estimated to be about 20 percent [4]. However, for other skin-related disorders, such as psoriasis and eczema, the mortality rate is much lower. Skin diseases are a common and growing problem, and computer-aided diagnosis (CAD) systems have been developed as a promising solution. Recent research studies have focused on developing CAD systems that can accurately diagnose skin diseases from digital images, such as dermoscopy images [5]. These systems use advanced deep learning algorithms to learn from a large number of training images, and then apply the learned knowledge to diagnose skin diseases from new images. The goal of the most recent research in this area is to improve the accuracy of the diagnosis. In this study the CNN model is a model used to classify skin diseases. It operates by extracting features from images of skin lesions and then classifying them according to type. The model is trained on a large dataset of images of known skin diseases. This allows the model to identify skin diseases with a high degree of accuracy. The model has a number of advantages over traditional methods of diagnosing skin diseases. For example, it is faster and more accurate than manual diagnosis, and it can detect a wide variety of skin conditions. Additionally, the CNN model does not require a large amount of data to be trained, as it is able to learn efficiently from a relatively small dataset. The CNN model is a powerful tool for diagnosing and predicting skin diseases. It has a number of advantages over traditional methods, such as being faster and more accurate. An ablation study has been performed in this study to get the fine-tuned CNN model.

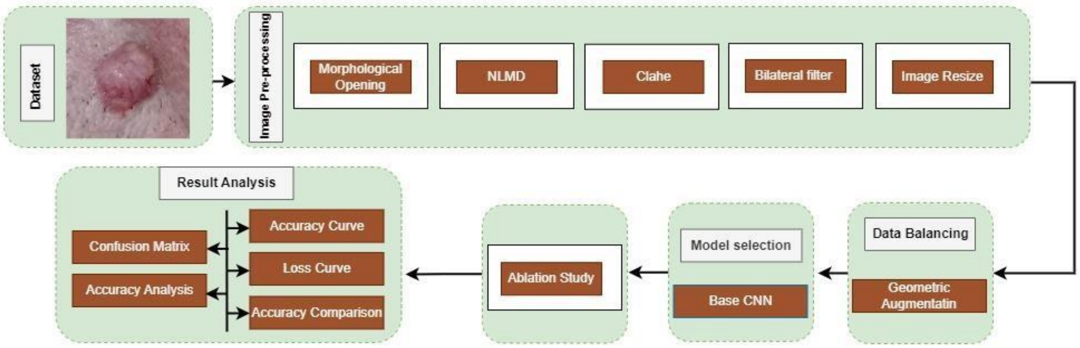

Figure 1. Working flow of the entire classification process

1.2 Motivation

We want to work with deep learning model because there are several motivations for using deep learning models in medical image prediction:

a) **Improved accuracy**: Deep learning models have the potential to achieve high levels of accuracy in medical image prediction, especially when large amounts of high-quality data are available for training.

b) **Automation**: Deep learning models can automate the process of predicting medical images, which can save time and reduce the need for human expertise.

c) **Personalization**: Deep learning models can be used to predict medical images for individual patients, which can enable personalized treatment plans.

d) **Efficiency**: Deep learning models can analyze large amounts of data quickly and accurately, which can improve the efficiency of the prediction process.

e) **Detection of subtle patterns**: Deep learning models can detect subtle patterns in medical images that might not be apparent to human observers, which can enable the early detection of diseases or other conditions.

Overall, the use of deep learning models in medical image prediction has the potential to significantly improve the accuracy and efficiency of the diagnosis and treatment of diseases and other medical conditions.

1.3 Rationale of the study

Over than 5.4 million cases of skin cancer are identified each year over the world, making it the most prevalent type of cancer. Early detection of skin cancer can lead to more successful treatment and improved patient outcomes. Many skin cancers, particularly melanoma, can be highly aggressive and can spread to other parts of the body if not caught in the early stages. By detecting skin cancer early, the chances of successful treatment are greatly increased. Early detection of skin cancer can also reduce the need for more aggressive and expensive treatment options, such as surgery or chemotherapy. Despite the high incidence of skin cancer, many people are unaware of the importance of regular self-examinations and screenings, or may not have access to these services. The study of early detection methods can help identify ways to increase awareness and access to screenings. The study of early detection methods can also help to identify risk factors for skin cancer and develop strategies for prevention, such as education about sun protection and promoting the use of sunscreen. By continuing to study and improve early detection methods for skin cancer, we can ultimately save lives and improve the overall health of the population.

1.4 Research Questions

Many different questions about this study could be asked in various ways. A series of questions were obtained from multiple people to make this study more compact.

1. How can we investigate research gaps in existing machine vision-based systems for correctly classifying different skin types?
2. How can we develop our proposed model approach for improving the accuracy for classify skin cancer according to their class?

3. What is the impact of early detection of skin cancer on patient outcomes and survival rates?

1.5 Expected Output

Deep learning is a new area of artificial intelligence-based research that has been developed with the purpose of bringing ML closer to one of its original goals, namely machine intelligence. This is why we wish to work with deep learning models. To deal with difficult input-output mappings, deep learning was created as an ML strategy.

1.6 Report Layout

This research report is broken into six distinct sections to make it more understandable and beneficial for readers and researchers.

Chapter 1 introduced this investigation. It's about tonsil cancer survival. This chapter covers research motivation, justification, relevant research topics, expected outcomes, management information, and financial issues.

In **Chapter 2** the context of this investigation is explained in detail. For instance, consider the categorization data from this research study, as well as the machine learning approaches and associated studies. This chapter discusses comparative analysis as well as the scope of this issue statement's predicted obstacles.

Chapter 3 is a full description of the methodology. This chapter offers information about the structure of this research endeavor.

Chapter 4 provides a full examination of each stage of the outcomes. This chapter also illustrates each result from the experiments.

Chapter 5 discusses the implications of this research for society, the environment, and long-term sustainability.

Chapter 6 shows this science's future. This chapter concludes the research report, summarizing its main findings.

CHAPTER 2

Background

2.1 Preliminaries:

Deep learning algorithms are trained on large datasets of skin images, labeled with the corresponding diagnosis. This allows the model to learn the various visual characteristics and patterns associated with different types of skin cancers, such as melanoma, basal cell carcinoma, and squamous cell carcinoma.

The accuracy of skin cancer detection using deep learning has been found to be highly competitive with that of expert dermatologists, and in some cases, even better. The use of deep learning in skin cancer detection has the potential to improve the speed, accuracy, and efficiency of skin cancer diagnosis, and could help save lives by detecting skin cancers early. Below some previous works are presented.

2.2 Related works

Ameri [5] offers a 2020 skin cancer diagnosis method using a deep convolutional neural network. He used the 3,400-image HAM10000 dermoscopy image database, which covers melanoma and non-melanoma lesions. Deep CNN was meant to classify images as benign or malignant. The lesion was neither dissected or extracted. Instead, CNN processed unedited photographs. We classified 84% of raw pictures. Yu et alautomated skin cancer detection method used deep convolutional neural networks (CNNs) trained on data from the ISBI 2016 Skin Lesion Analysis toward Melanoma Detection Challenge. Since their network included over fifty layers, the recommended method was more accurate than earlier approaches. Their network became richer and more discriminative, improving performance. A fully convolutional residual network (FCRN) segmented skin lesions, and very deep residual networks categorized them. It had two phases. Their network was deeper than others', and they obtained 85.5% classification accuracy with less training data. This distinguished their research. Their study suggested that segmentation may improve results over direct modification of dermoscopic images. Andre Esteva et al. [7] classified skin lesions using deep convolutional neural networks. The CNN was trained using just pixel values and sickness diagnoses from 129,450 clinical pictures. They then compared its effectiveness to 21 board-certified dermatologists using biopsy-proven clinical pictures. AI algorithms can detect skin cancer as well as dermatologists. [Cite] Melanoma images had 94% accuracy, carcinoma images 96%, and dermoscopic images 91%. The CNN's sensitivity and specificity curve showed promise, but the false positive and false negative rates were excessively high. Jinnai et al. [8] employed deep learning to categorize pigmented skin lesions as benign or malignant skin cancers. Faster region-based CNN (FRCNN) was applied to 5,846 clinical images from 3,551 patients. The FRCNN classified into six classes with 86.2% accuracy and two classes with 91.5% accuracy (benign or malignant). The FRCNN outperformed both dermatologists and other methods. Boman and Volminger proposed a deep convolutional neural network model for skin cancer classification in 2018 [9]. They compared melanoma to solar lentigo and seborrheic keratosis to test CNN's diagnosis. They relied extensively on the 23,647-image ISIC Dermoscopic Archivedataset. They also downloaded 16,826 photos from DermQuest, 4,336 from the Dermatology Atlas, 1,948 from DermaAmin, Dermoscopy Atlas, Global Skin Atlas, Hellenic Dermatological Atlas, Medscape, Regional Derm, Skinsight, and pH2. 16-way and three-way classifications were employed to assess accuracy. The binary classification of seborrheic keratosis versus basal comparison exhibited the best accuracy (91%). This demonstrated that deep learning classifiers can attain binary comparison accuracy. Rehan Ashraf et al. [10] proposed a 2020 transfer learning-assisted skin cancer detection framework. This framework used intelligent ROI. Deep learning methods that use full photos for feature learning may not extract discriminative features well. Since ROI-based techniques only utilize that section of the image to train the system, they may find discriminative features. To extract ROIs from pictures, they adjusted k-mean. After that, they created a CNN-based transfer learning model for ROI photos with data augmentation. 77% of the data was used for training and 23% for testing. The ROI-based technique categorized their first dataset at 97.9% and their second dataset at 97.4%. The ROI-based technique beat global feature-based classification algorithms. Goyal et al. [11] recommended employing dermoscopic photos to find areas of interest (ROI) for data augmentation in 2018. They found ROI skin lesions in dermoscopic images using CNN (Faster-RCNN) and two object localization meta-architectures. According to their experiments, their skin localization methods worked better than segmentation methods for skin lesions. ROIs may enhance lesion localization and dataset quality. The FRCNN (Faster-RCNN) Inception V2 method outperformed other models with 94.5 percent accuracy and 94.3 percent recall on the ISBI-2017 testing dataset. Dermoscopy located the ROI. FRCNN performed best on new datasets in accuracy and recall, proving its validity. Ali et al. [12] suggested a fuzzy method-based multilayer perceptron (F-MLP) system for skin lesion boundary irregularity detection in 2020. Since border irregularity is a skin cancer indicator, our technique helped detect melanomas early. ANNs and MLPs excel at supervised learning. However, the way weights are adjusted during learning might alter the network's performance on test data. They created a fuzzy multilayer perceptron (F-MLP) to reduce the influence of unclear inputs on learning. Their technique outperformed most categorization methods, including its neural network-based equivalent. F-MLP performed best with an 80:20 training-to-testing ratio. 95.2% accuracy. Our recommended fuzzy neural network took longer to train than a standard neural network. Fujisawa et al. [13] described autonomous deep learning-based skin cancer classification in mid-2019. ILSVR2012, with 1.2 million pictures in 1,000 categories, was used. They also showed that feature extraction may boost model performance and efficiency. A deep learning-based convolutional neural network (CNN) generated the best results for them when they employed their feature values since it can learn and automatically identify which features are significant for classification based on the training picture set. The CNN model had an accuracy of 75% for the 14-class classification and 92% for the two-class classification, greater than board-certified dermatologists. Combining convolutional neural networks and textural features, Seyed Mohammad Alizadeh and colleagues [14] proposed an autonomous skin cancer diagnostic approach using dermoscopic photos. They analyzed ISIC 2016, ISIC 2019, and PH2. After preprocessing the pictures using the DullRazor method [15], texture features were retrieved and their dimension decreased using kernel principal component analysis (kPCA) to improve classification performance in the feature extraction-based phase. In the CNN phase, their proposed network and VGG-19-two CNN models classified pictures. The ensemble technique used the findings of these two processes to calculate the final conclusion. For three datasets, this automated technique had

85.2%, 96.7%, and 97.5% accuracy. Maad M. Mijwil [22] used CNN (ConvNet) to analyze 24,000 skin cancer pictures. He employed InceptionV3, ResNet, and VGG19 to classify pictures as benign or cancerous. The author utilized high-resolution photos from the ISIC archive in their 2019–2020 study. The top architecture, InceptionV3, has 86.90% greater diagnostic accuracy. Ranpreet Kaur et al. [16] developed the lesion classification network (LCNet) DCNNmodel to classify malignant and benign melanoma. This model used International Skin Imaging Collaboration datastore dermoscopic images (ISIC2016, ISIC2017, and ISIC 2020). Three datasets yielded 81.41 percent, 88.23 percent, and 90.42% accuracy. They had lesser accuracy since they did not use substantial preprocessing or ROI to extract lesion features. Hatice Catal Reis et al. [17] used International Skin Imaging CollaborationHAM10000 pictures (ISIC 2018), ISIC 2019, and ISIC 2020 datasets to construct a deep learning-based CNN algorithm to identify benign and malignant lesions. This model distinguished benign from malignant lesions. The GoogleNet Inceptionmodule built this model. Fewer criteria and medical photographs reduced diagnostic time. Meta-heuristic algorithms and graph techniques might have improved segmentation studies for more in-depth diagnostic outcomes. This would have improved data interpretation. Over three datasets, this basic model achieved 94.59%, 91.89%, and 90.54% accuracy. Bechelli et al. [18] utilized machine learning and deep learning to classify dermoscopic skin cancer images as benign or malignant. The research study uses ISIC archive and HAM10000. Machine learning methods LR, LDA, KNN, CART, and GNB solved the classification issue. The mean prediction result utilized the maximum variety, average forecast, and top performance. The research's deep learning model included exception, VGG16, and ResNet50 networks. Later models were modified to improve predictions. Accuracy, precision, recall, F-score, FPR, and ROC curve help evaluate prediction results. Ensemble machine learning's precision score is 0.79 and f-score is 0.70. After the adjustments, VGG16, ResNet50, and Xception have f-scores of 0.69, 0.61, and 0.50.

2.3 Comparative Analysis and Summary:

In this case, we can see that the results of our model are the highest compared to other cancers, which proves the acceptability of our model.

Table 1: Comparative Table

Reference	Year	Model	Accuracy
Proposed	2022	SkinNet-11	98.00%
[5]	2020	Deep CNN	84.00%
[6]	2017	Convolutional residual network (FCRN)	85.5%
[7]	2017	CNN	96.00%
[8]	2020	CNN(FRCNN)	91.5%
[9]	2018	CNN	91.00%

2.4 Scope of the Problem:

Within the scope of this research project, a suggested computer-aided diagnosis (CAD) system for skin diseases divides skin conditions into six distinct categories. The noise and artifacts that were present in the images utilized in this experiment were eliminated by the use of several picture pre-processing methods. Image improvement strategies were used in order to further improve the overall image quality of the raw skin disease photographs. Experiments with a fundamental CNN model were done in order to evaluate its performance. A model called SkinNet-11 that uses Basis CNN as its fundamental base has been suggested. In order to test and enhance the robustness of the model, an ablation research is carried out on the network that we have suggested.

2.5 Challenges: The most challenging aspect of this research is finding the appropriate dataset. On the internet, there are many datasets, however, most of them are uneven. Not least of all, we selected the PAD-UFES dataset. After that we use Image Processing technique for processes the image. Although this dataset has some inconsistencies as well, we choose to use it anyhow in order to enhance the outcomes. Due to our GPU configuration's limitations, training the model presented additional difficulties.

CHAPTER 3

Research Methodology

3.1 Research Subject and Instrumentation:

Our research subject is skin cancer detection system. Because skin cancer detection using deep learning is a rapidly growing area of research that utilizes artificial intelligence techniques to identify the presence of skin cancers. This method involves the use of deep neural networks to analyze images of skin lesions and determine whether they are malignant or benign.

Skin diseases are a global health issue affecting all ages, ethnicities, and socioeconomic backgrounds. One-third of all cancers are skin cancers, and the incidence has increased in recent decades. Skin cancer affects over 5 million people in 2019. Mortality rates vary based on type, severity, and patient factors. CAD systems using deep learning algorithms show promise in accurately diagnosing skin diseases from digital images. A CNN model was used to classify skin diseases by extracting features from images and training on a large dataset. The model is faster, more accurate, and can detect a variety of skin conditions, even with a small training dataset. The CNN model is a powerful tool for skin disease diagnosis and prediction. An ablation study was performed to fine-tune the model.

3.2 Data Collection Procedure:

The PAD-UFES dataset contains 2298 images which were used in this study. Actinic keratosis, melanoma, basal cell carcinoma, nevus, squamous cell carcinoma, vascular lesions, nevi and seborrheic keratosis are the six types of skin cancer in the dataset. The actinic keratosis category contains 730 images, the basal cell carcinoma category contains 845 images, the melanoma category contains 52 images, the nevus category contains 244 images, the seborrheic keratosis category contains 192 images, and the squamous cell carcinoma category contains 235 images. All photos in the datasets are 1050 x 1050 pixels. In Table 1 we see a summary of the data sets:

Table 2: Dataset Description

Name	Description
Total Number of Images	2298
Dimension	1050 x 1050
Data Formats	JPG
Actinic Keratosis	730
Basal Cell Carcinoma	845
Melanoma	52
Nevus	244
Seborrheic Keratosis	192
Squamous Cell Carcinoma	235

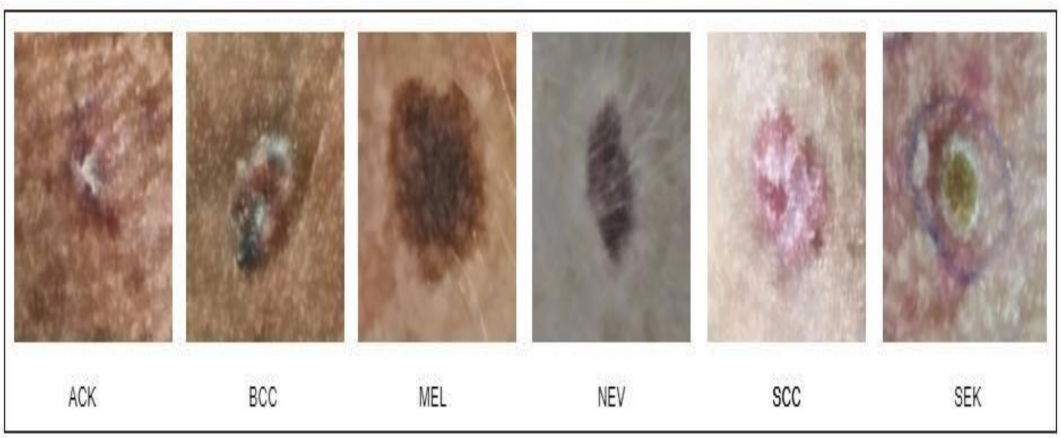

Figure 2. Skin Cancer dataset with six classes.

3.3 Statistical Analysis:

For statistical analysis we have used confusion matrix the equation of those given below [35].

$$ACC = \frac{TP+TN}{TP+TN+FP+FN} \quad (12)$$

$$Recall = \frac{TP}{TP+FN} \quad (13)$$

$$Specificity = \frac{TN}{TN+FP} \tag{14}$$

$$Precision = \frac{TP}{TP+FP} \tag{15}$$

$$ACC = 2\frac{precision*recall}{precision+recall} \tag{16}$$

3.4 Applied Mechanism/Proposed Methodology:

In below here is our applied mechanism and our proposed methodology.

3.4.1 Image pre-processing:

Preprocessing images before putting then into a neural network optimizes the model's performance. This study uses different widely used techniques to remove artifacts and enhance image quantity. Firstly, morphological opening is applied to removes artifacts, Non-Local Means Denoising (NLMD) is introduced to minimize noise and CLAHE to improve brightness and contrast. At last bilateral filter is used for smoothing pixels.

a. Artifact Removal:

Morphological opening [20] is a technique which eliminates all single pixel artifacts such as tiny small objects, glob, spurs. It works by applying a morphological filter to the image that erodes away small features. This is done by transforming the image into a binary image and then applying a structuring element to the image. The structuring element is a small window that is used to compare the pixels in the image. Pixels that lie within the window are identified as noise and are removed. This process is repeated until all of the noise has been removed. The result is an image with reduced noise and better clarity. Morphological opening is often used in medical imaging applications to reduce the amount of noise in skin cancer images.

Figure 3. Output of the morphological dilation

b. Clahe:

CLAHE [21][34] (Contrast Limited Adaptive Histogram Equalization) is an image processing technique used to improve the visual appearance of an image. It works by adjusting the contrast of an image by redistributing the lightest and darkest pixels in order to increase the overall contrast. Unlike traditional histogram equalization, CLAHE works on a local level, meaning that the contrast adjustments are made on a small region of the image. This prevents areas of the image from becoming over- or under-saturated due to global adjustments. CLAHE is particularly helpful for medical imaging and digital photography, as it is capable of preserving details that may otherwise be lost due to global contrast adjustments. Additionally, it can help bring out detail in low contrast images, such as those taken in low light, and can improve the visibility of otherwise invisible patterns in an image. Overall, CLAHE is a powerful image enhancement tool that can be used to improve the visual appearance of an image. It is particularly useful in medical imaging and digital photography [24], as it is capable of preserving detail and improving visibility of patterns in an image.

Figure 4. Output of the Clahe

c. NLMD:

Nonlocal Means Denoising (NLMD) is an image denoising technique that uses self-similarity to reduce noise from an image. NLMD works by comparing each pixel in an image to similar pixels in a neighborhood, creating a "patch" of similar pixels. The denoising algorithm then takes the average of the patch and replaces the original pixel values with the average, thus reducing the noise. NLMD is particularly useful for denoising images that have a lot of noise, such as those taken in low-light environments or with a high ISO setting. NLMD is a powerful denoising method that produces excellent results. It is also computationally efficient and easy to implement, making it a popular choice for many applications. NLMD is also able to preserve edges and details in an image, which makes it a great option for denoising photographs. Overall, NLMD is a powerful and efficient image denoising technique that can produce excellent results with minimal computational effort. It is particularly well-suited for denoising photographs taken in low-light environments or with a high ISO setting.

Figure 5. Output of the NLMD

d. Bilateral filter:

Bilateral filter is often used to reduce noise and detail in an image while preserving edges. The filter is based on a weighted average of each pixel's neighborhood, where pixels closer to the center pixel have a higher weight. The weights are based on the spatial distance (distance from the center pixel) and a measure of the pixel intensity difference, or color similarity. This allows the filter to preserve edges, since pixels with a large intensity difference are not averaged together. The filter can be used to reduce noise and blur details, while preserving edges. It is often used in image processing applications such as denoising, smoothing, and sharpening. It is also used in medical imaging, where it can help to reduce artifacts and improve the diagnostic quality of images. The filter is also useful for creating stylized images, where it can be used to create a soft, dreamy look.

Figure 6. Output of the Bilateral filter

e. Image Resize:

Image resizing is an important image processing technique used in a variety of applications, including medical imaging, computer vision, image compression, and image retrieval. Image resizing involves changing the size of an image by scaling it up or down to fit a desired dimension. This can be done by changing the number of pixels in the image, or by changing the aspect ratio of the image.

Figure 7. Output of the image resize

3.4.2 Verification:

Many image preprocessing procedures may cause the potential to significantly degrade image quality; hence, numerous numerical evaluations are used to ascertain whether or not the images have suffered from quality loss.

a. MSE:

The pixels in the two images that are being compared have a cumulative squared error, as stated by MSE. Values that are quite near to 0 indicate an exceptional image quality. Pictures that are free of noise have a value of 0. If the number is more than 0.5, it implies that the quality has decreased.

$$MSE = \frac{1}{xy}\sum_{i=0}^{m-1}\sum_{j=0}^{n-1}(O(m,n) - P(m,n))^2 \quad (7)$$

Where,

O is the ground truth (original image), P is the processed image, x and y denote the pixels of O and P, and m, n denote the rows of the pixels x, y.

b. PSNR:

PSNR (Peak Signal-to-Noise Ratio) is a metric used to measure the quality of a reconstructed signal compared to the original signal. It is calculated by taking the ratio of the maximum possible signal power to the power of the noise in the reconstructed signal. This ratio is usually expressed in decibels (dB) and is a measure of the signal-to-noise ratio (SNR). The higher the PSNR value, the better the quality of the reconstructed signal. PSNR values of 30 dB or higher indicate an excellent quality reconstruction, while values below 20 dB indicate poor quality. PSNR is commonly used to measure the quality of image and video compression algorithms, as well as audio and speech coding algorithms.

$$PSNR = 10 \log_{10}\left(\frac{Q^2}{MSE}\right) \tag{8}$$

The input image data type Q has the highest fluctuation. The max is 255 pixels [26].

c. SSIM:

Structural Similarity Index (SSIM) is a method of measuring the similarity between two images. It is based on the fact that the perceived quality of an image is largely determined by its structural similarities. SSIM is calculated by comparing the luminance, contrast, and structure of the two images. It measures the relative amount of similarity between two images, and can be used to compare images of different sizes or formats. Preprocessing algorithms reduce image quality, as measured by SSIM. A score of 1 reveal "perfect structural similarity" and a result of 0 indicates no structural similarity [26].

$$SSIM(x,y) = \frac{(2\mu_x\mu_y + c_1)(2\sigma_{xy} + c_2)}{(\mu_x^2 + \mu_x^2 + c_1)(\sigma_x^2 + \sigma_x^2 + c_2)} \tag{9}$$

Where,

x, y is two image, σ^2_x, σ^2_y is variance, σ_{xy} is covariance of the images and μ_x, μ_y is the average of two image calculated using the Gaussian window.

d. RMSI:

RMSI (root mean square intensity) measures image intensity. In image processing, it measures contrast or the difference among an image's foreground and background. It measures image brightness and is used to establish the ideal exposure settings. RMSI is the square root of the image's pixel intensity values' squares. This value is divided by the image's pixel count to get the average intensity. RMSI increases visual contrast. RMSE compares original and processed images to determine picture quality. Good images have low RMSE values.

$$RMSE = \sqrt{\sum_{J=1}^{N}(d_{fi} - \frac{d_d)^2}{N}} \quad (10)$$

Where, d_{fi} is the different of predict value, d_d is the actual value, N is the Size of the Dataset

Table 3. MSE, PSNR, SSIM, RMSE value for 5 images

Image	MSE	PSNR	SSIM	RMSE
Image_1	11.72	37.46	0.97	0.13
Image_2	11.43	32.89	0.97	0.13
Image_3	11.48	41.36	0.96	0.10
Image_4	14.52	36.29	0.95	0.13
Image_5	11.34	37.47	0.96	0.12

3.4.3 Data Augmentation:

Geometric augmentation is a technique used in image processing to modify an image by adding or changing geometric features. This is done by applying a transformation to the image that alters the position, size, orientation, or shape of the image. In this study we are employed 4 geometric augmentation techniques like vertical flipping, horizontal flipping, rotation into 45 degree and rotation into 90 degrees.

3.4.4 Data Split:

Data split is a process used to divide data into separate parts for testing and training purposes. The purpose of data splitting is to ensure that the results of the tests on a given data set are accurate. A good data split should have a representative sample of the data set for testing and training. This ensures that the results of the tests are not skewed by having too much data from one particular set. Before training, the dataset must be split. Based on the size of the training and testing data, there are three common ways to measure how accurate a model is: 90:10, 80:20, and 70:30. According to a recent study [27], 20% of the dataset was used as the test dataset. The images in the skin cancer augmented dataset have been split into three sets with a 70:10:20 split between the training, validation, and test sets, respectively.

3.4.5 PROPOSED METHODOLOGY

As stated before, five models were investigated in order to find the most effective transfer learning model for the categorization problem. Each of these networks was trained using the training data and then put to the test using the testing data.

a. VGG16:

Various computer vision applications have made use of VGG 16, one of the superior image prediction models that is also very effective and simple to use. The DCNN model named as VGG16 was first introduced by Simonyan and Zisserman [28]. In many applications, it serves as the basis model because of its great results on the ImageNet dataset. Its key benefit is its ability to be trained on a minimal amount of data while still performing well. Studies on the effectiveness of transfer learning have shown that a pre-trained VGG16 provided accuracy that was significantly higher than a properly trained network [30]. The deeper the VGG model, the more intricate traits the kernel may learn.

b. VGG19:

VGG19 is a convolutional neural network model that was developed by the Visual Geometry Group (VGG) at the University of Oxford. It was trained on the ImageNet dataset, which consists of millions of labeled images from a wide variety of categories. VGG19 is a 19-layer model with a deep convolutional architecture. The model was designed to recognize and classify images with high accuracy. The model consists of 13 convolutional layers and 5 fully-connected layers. Each convolutional layer is followed by a batch normalization layer and a ReLU activation layer.

The model also contains a max-pooling layer, which is used to reduce the size of the feature maps.

c. MobileNet:

MobileNet is a deep learning model developed by Google for the purpose of providing an efficient, low latency mobile vision solution. It is a lightweight convolutional neural network (CNN) designed to run efficiently on mobile and embedded devices, such as smartphones, tablets, and embedded vision applications. MobileNet is designed to be computationally efficient and to reduce latency by minimizing the number of network operations per frame. It achieves this by replacing multiple convolutional layers with depth-wise separable convolution layers, which reduces the number of parameters and computational operations while still maintaining accuracy. The model is based on an architecture that uses a combination of 1×1 and 3×3 convolutional layers, with the 1×1 layers used to reduce the number of parameters and the 3×3 layers used to increase the network's receptive field. The network also uses a global average pooling layer at the end of the network to reduce the dimensionality of the feature vector.

d. MobileNetV2:

MobileNetV2 is a light-weight convolutional neural network designed to run efficiently on mobile devices. It is an improved version of MobileNetV1, which was designed to achieve high accuracy while keeping model size and computational complexity low. MobileNetV2 has a more efficient architecture than its predecessor, allowing it to achieve higher accuracy when run on the same hardware. It is also designed to be more robust to adversarial attacks and other types of input noise. In addition to the improved accuracy and robustness, MobileNetV2 is designed to conserve battery life and reduce latency on mobile devices. This makes it especially suitable for use in applications such as object detection and image segmentation. MobileNetV2 is also compatible with existing models and can be used as a drop-in replacement for MobileNetV1.

e. InceptionV3:

Inception V3 is a convolutional neural network architecture developed by Google for the ImageNet Large Visual Recognition Challenge in 2015. It is a deep learning model that combines elements from different types of neural networks and is designed to capture both local and global features of an image. It was the winning entry of the ImageNet challenge in 2015 and is widely used for image classification tasks. The Inception V3 architecture consists of multiple modules, each of which is designed to capture a different type of feature from the input image. It is composed of a stack of convolutional layers, pooling layers, and fully connected layers. The convolutional layers are used to capture the local features of an image, while the pooling layers are used to capture the global features. The fully connected layers are used to combine the local and global features to produce a prediction. Inception V3 is widely used for image classification tasks due to its impressive results on the ImageNet challenge. It is also used in other applications such as object detection, image segmentation, and image generation. In addition, Inception V3 is also used in transfer learning, where a pre-trained model is used as a starting point for training a new model.

f. Base CNN:

Base CNN model has 4 convolutional and 4 maxpool layers where flatten layer is used initially. In the initial state the model is set to batch size 16 and optimizer Adam. 0.001 is set as the learning rate of Base CNN model. A diagram of the Base CNN model can be found below:

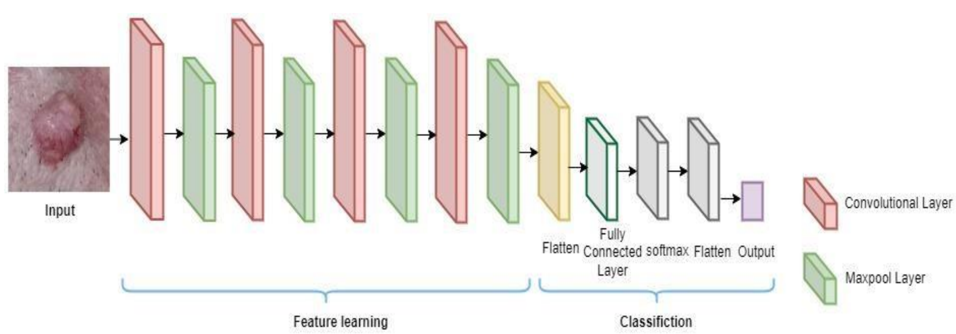

Figure. 8 Base CNN Model

g. Training Approach:

In order to train the models, the batch size is 16, and the maximum number of epochs is 400 [31]. A minimal loss value was used to store the weights of the best model during training [31]. At a learning rate of 0.001, Adam has been used as an optimizer.

Multiclass problems are typically solved using categorical cross-entropy [31]. A 'SoftMax' activation is used to forecast the probability for each class. All values between 0 and 1 are normalized by SoftMax, so their aggregate is always 1.

h. Ablation study:

In CNN-based applications, an ablation study is often conducted to assess the model's stability and performance after deleting or changing various layers or hyperparameters. In this study, hyperparameter ablation is used to generate robust and fine-tuned networks. In this study, there are 5 case study has experimented on the skin disease preprocessed dataset.

i. SkinNet-11:

Through the ablation study, a robust model (SkinNet-11) is generated by changing the layers and parameters of the base CNN model. SkinNet-11 consists of 3 blocks, with the first block having one convolutional and two maxpool layers. As for the second block, there are two convolutional and two maxpool layers. On the other hand, the third layer consists of two convolutional and one maxpool layer. After that there is a flat layer and a fully connected layer in the proposed SkinNet-11 model.

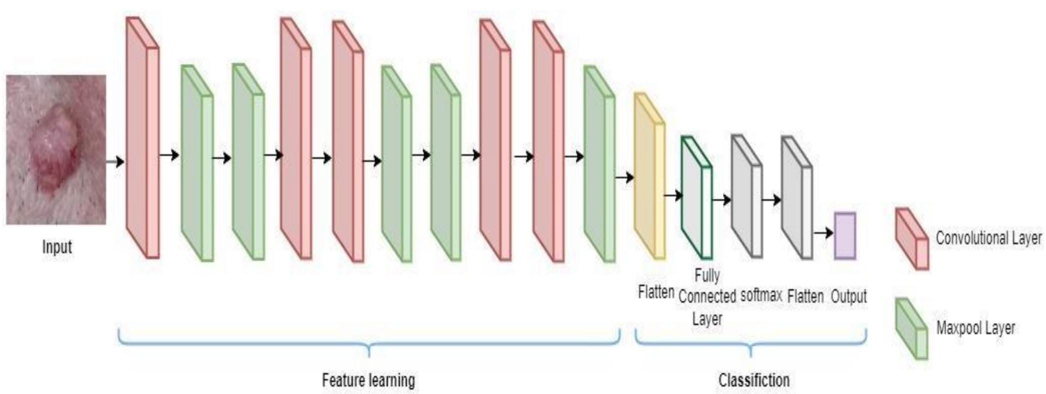

Figure.9 SkinNet-11 Model

3.5 Implementation Requirements:

I. Laptop

II. Internet Connection.

III. Kaggle.

IV. Python Environment.

V. Fast-ai.

CHAPTER 4

Experimental Results and Discussion

4.1 Introduction and Experimental Setup:

In order to test different models and configurations, we used three PCs, each of which has an Intel Core i5-8400 processor, 16 GB of RAM, an NVidia GeForce GTX 1660 GPU, and a 256 GB DDR4 SSD for storage.

4.2 Experimental Results and Analysis:

Several design components can be changed to improve classification accuracy. A total of six experiments are run as an ablation study, modifying various elements based on the base CNN architecture. The results of the Ablation Study are shown below:

Scenario 1: Changing convolutional and maxpool layer

Table.4 Changing convolutional and maxpool layer

Case Study 01					
Configuration No.	**No. of convolution layer**	**No. of pooling layer**	**Epoch x training time**	**Test accuracy (%)**	**Finding**
1	2	2	293 x 59s	88.22%	Least accuracy
2	3	3	295 x 56s	91.63%	Least accuracy
3	4	4	390 x 56s	90.69%	Least accuracy
4	**5**	**5**	**289 x 54s**	**94.43%**	**Best accuracy**

Scenario 2: Changing Pooling Layer

According to case study 1, the flatten layer provides the highest level of accuracy. Additionally, both global averages and global maximums do not provide good accuracy. 93.43% accuracy is obtained when the layer is flattened, while 95.98% and 95.32% accuracy are achieved when the layer is summed up globally.

Table 5. Altering Pooling layers

		Case Study 02		
Configuration No.	**Pooling layer types**	**Epochs x training times**	**Test_accuracy (%)**	**Findings**
1	**Flatten**	**192 x 55s**	**95.43.%**	**Highest accuracy**
2	Global Max pooling	274 x 58s	93.98%	Accuracy_dropped
3	Global Average pooling	260 x 56s	93.32%	Accuracy_dropped

Scenario 3: Changing the batch size

Case study two deals with changing the batch size. The most accurate batch size is 32, followed by 32, 64, and 16. When the batch size is 32 the test accuracy is 97.52%.

Table 6. Altering the batch sizes

		Case Study 03		
Configuration No.	**Batch size**	**Epochs x training times**	**Test_accuracy (%)**	**Finding**
1	16	295 x 87s	96.43%	Modest accuracy
2	**32**	**243 x 52s**	**97.52%**	**Highest accuracy**
3	64	282 x 44s	94.61%	Modest accuracy

Scenario 4: Loss Function change

As a result of experimenting with different loss functions, case study 3 finds that categorical cross-entropy produces the best results, 97.52%.

Table 7. Altering losses functions

		Case Study 04		
Configuration No.	Loss Functions	Epochs x training times	Test_accuracy (%)	Findings
1	**Categorical Crossentropys**	**297 x 55s**	**97.52%**	**Highest accuracy**
2	Mean Squared Errors	396 x 58s	95.56%	Accuracy dropped
3	Mean absolute errors	212 x 54s	94.95%	Accuracy dropped

Scenario 5: Optimizer change

Adam optimizer provides the highest accuracy when compared to Nadam, SGD, and Adam ax optimizers in case study 4.

Table 8. Altering optimizers

		Case Study 05		
Configuration No.	Optimizers	Epochs x training times	Test_accuracy (%)	Findings
1	**Adam**	**297 x 56s**	**97.52%**	**Highest accuracy**
2	Nadam	244 x 53s	96.88%	Previous dropped
3	SGD	290 x 52s	96.65%	Accuracy dropped

Scenario 6: Learning Rate change

In comparison to 0.001, 0.0001, and 0.01, when using 0.01 provide the highest accuracy.

Table 9. Altering learning rates

		Case Study 06		
Configuration No.	Learning rates	Epochs x training times	Test accuracy (%)	Findings
1	0.01	262 x 55s	97.52%	Accuracy dropped
2	**0.001**	**196 x 56s**	**98.00%**	**Highest accuracy**
3	0.0001	285 x 57s	97.29.%	Accuracy dropped

4.2.1 Performance Analysis of Best Model:

A summary of CNN's final setup is provided in Table 9.

Table 10. Configuration of our models

Configuration	**Value**
Image sizes	224 x 224
Epochs	400
Optimization Functions	Adam
Learning rates	0.001
Batch sizes	32
Activation functions	Softmax
Dropouts	0.5
Momentums	0.9
Accuracy	**98.00%**

4.2.2 Performance Analysis and Statistical Analysis:

As shown in table 10, the most hyper-tuned and robust CNN model has the following class-based precision, recall and f1-score.

Table 11. Performance Analysis and Statistical Analysis

Class	Precision	Recall	F1-score	Accuracy
ACK	0.98	0.98	0.98	0.98
BCC	0.99	0.98	0.98	
MEL	0.93	1.00	096	
NEV	0.99	0.99	0.99	
SCC	0.93	0.97	0.95	
SEK	0.99	0.99	0.99	

4.2.3 Confusion Matrix, Accuracy and Loss Curve:

A confusion matrix is a table that is often used to describe the performance of a classification model (or "classifier") on a set of test data for which the true values are known. It allows the visualization of the performance of an algorithm. The confusion matrix is an N x N matrix, where N is the number of target classes. Each entry of the matrix is the number of observations known to be in a certain class but predicted to be in a different class. The confusion matrix is a way of summarizing the performance of a classification algorithm. The matrix consists of four cells, each representing the number of predictions a particular algorithm got right and wrong. The rows of the matrix represent the true classes and the columns the predicted classes. The top left cell of the matrix represents the true positives, that is, the number of observations that were correctly classified as belonging to the target class. The top right cell represents the false positives, that is, the number of observations that were incorrectly classified as belonging to the target class. The bottom left cell represents the false negatives, that is, the number of observations that were incorrectly classified as not belonging to the target class. The bottom right cell of the matrix represents the true negatives. In Figure 10 shows the Confusion matrix for the best-performing model.

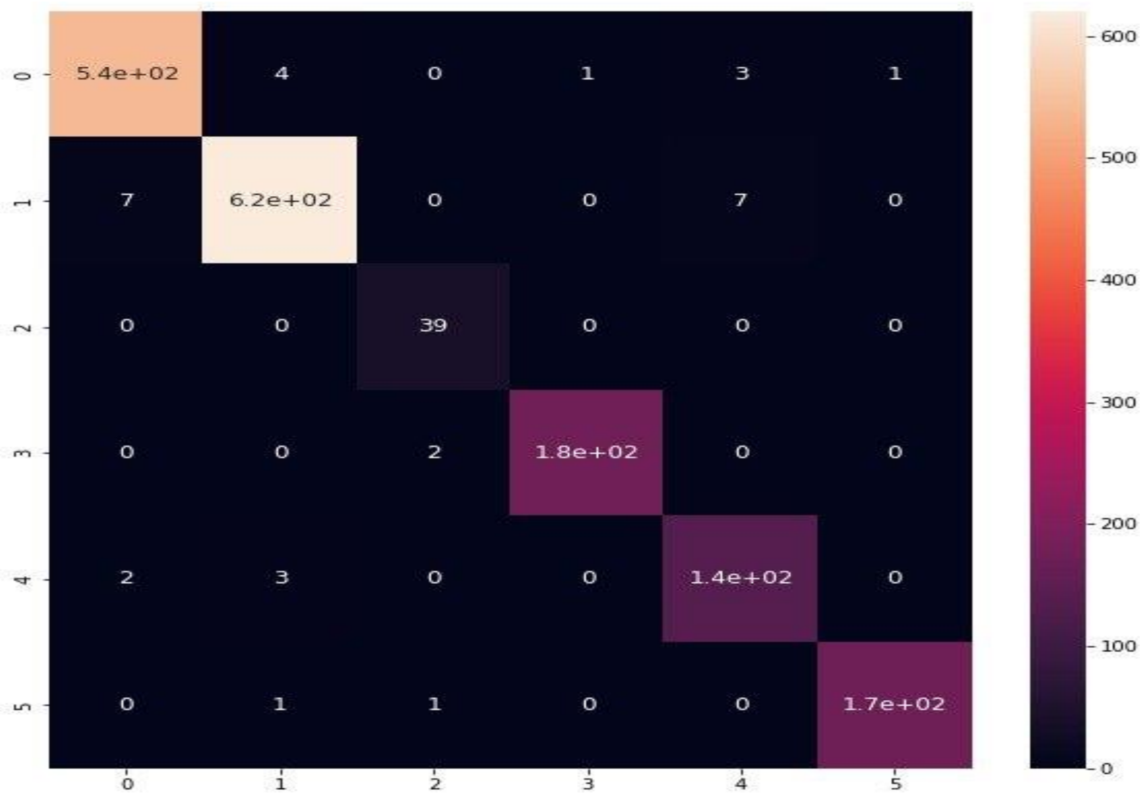

Figure 10. Confusion Matrix for the best-performing model.

Loss curve and accuracy curve are two performance metrics used to evaluate the effectiveness of a model. The loss curve is a graph that shows the total loss of a model over a given number of training iterations or epochs. This metric is used to measure how well a model is able to minimize the total loss of its training samples. The accuracy curve is a graph that shows the accuracy of a model over a given number of training iterations or epochs. This metric is used to measure how well a model is able to predict the correct output for its input data. Both of these metrics are useful in determining the quality of a model and help guide decisions on how to improve it.

In Figure 11 shows the accuracy and loss curves for the best-performing model.

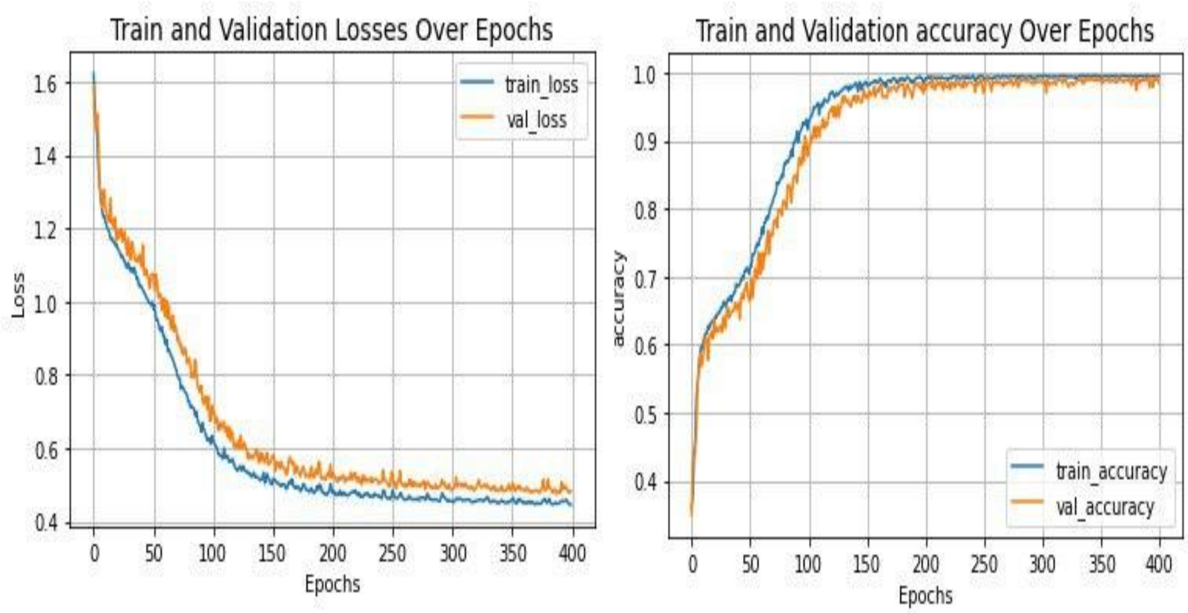

Figure 11. The Loss curve and Accuracy curve

4.3 Discussion:

In the Table 11 shows the accuracy (training, testing and validation), and loss (train, test and validation) for the five transfer learning models.

Table 12. Result of five transfer learning model and proposed model

Model	**Epoch**	**Val_Accuracy**	**Val_loss**	**Test_Accuracy**	**Test_loss**
VGG16	400	0.83069	0.4217	85.02	0.5550
VGG19	400	87.18	0.331	82.58	0.7666
Mobile Net	400	91.13	0.8038	82.39	3.659
Mobile Net V2	400	80.06	0.4217	76.04	0.5550
InceptionV3	400	83.67	0.4252	82.57	0.5678
SkinNet-11	**400**	**98.00**	**0.3822**	**98.00**	**0.4288**

CHAPTER 5

Impact on Society, Environment and Sustainability

5.1 Impact on Society:

Early detection of skin cancer is important because it can lead to more successful treatment and can potentially reduce the number of deaths caused by the disease. When skin cancer is detected in its early stages, it is usually much easier to treat and the chances of a full recovery are much higher. This can have a significant impact on individuals and their families, as well as on society as a whole. Early detection can also help to reduce the financial burden on the healthcare system, as the cost of treating advanced skin cancer is often much higher than the cost of treating early-stage skin cancer.

5.2 Impact on Environment:

There is no direct impact of skin cancer early detection on the environment. However, the treatment of skin cancer can have an impact on the environment, depending on the methods used. For example, some skin cancer treatments may involve the use of chemotherapy drugs, which can be harmful to the environment if they are not disposed of properly. In addition, the production and transportation of these drugs can also have an environmental impact. However, early detection of skin cancer can help to reduce the overall environmental impact of the disease by reducing the need for these treatments and the resources that are required to deliver them.

5.3 Ethical Aspects:

There are several ethical aspects to consider when it comes to early detection of skin cancer. One issue is access to screening and treatment. Some people may not have access to high-quality skin cancer screening and treatment due to financial or geographical barriers. This can create inequities in care and may disproportionately affect marginalized or underserved populations. Ensuring that all people have access to screening and treatment for skin cancer is an ethical responsibility of the healthcare system.

Another ethical issue is informed consent. Patients should be fully informed about the benefits and risks of skin cancer screening and treatment, and they should be given the opportunity to make decisions about their care based on this information. This includes ensuring that patients understand the potential side effects of treatments and the limitations of screening tests.

Additionally, there are ethical concerns around the use of personal data in skin cancer screening and treatment. Personal medical information, including information about skin cancer diagnosis and treatment, should be kept confidential and protected. There may be situations where this information needs to be shared with other healthcare providers or researchers, but this should only be done with the patient's knowledge and consent.

5.4 Sustainability Plan:

A sustainability plan for early detection of skin cancer might include a range of strategies to ensure that screening and treatment programs are available to all people, regardless of their ability to pay or where they live. This could involve:

1. Implementing policies and programs to reduce financial barriers to care, such as providing financial assistance or subsidies to help people afford screening and treatment.

2. Increasing access to care by expanding the availability of screening and treatment services in underserved areas, including rural and remote communities.

3. Promoting the use of technology to increase the efficiency and reach of screening and treatment programs, such as using telemedicine to connect patients with healthcare providers remotely.

4. Working with community organizations to educate people about the importance of skin cancer prevention and early detection, and to provide information about available screening and treatment options.

CHAPTER 6

Summary, Conclusion, Recommendation and Implication for Future Research

6.1 Introduction:

This chapter discussed how the project's potential can effectively support the organization's future growth. A more efficient way might be created using future technologies. A pleasant and orderly conclusion is presented at the end of this chapter. A list of the references is provided at the conclusion of this chapter.

6.2 Implication for Further Study

We will collect a significant amount of data from a large number of really reliable sources and use a productive pre-processing strategy to make sure that no important data is lost. Analyze more strategies for handling uneven data. We implemented new deep learning algorithms and identified highly correlated features in order to get better results. It is feasible to ensure that the recommended fine-tuned SkinNet-11 model is accurate and improved in all areas of diagnosis.

6.3 Conclusion

Within the scope of this research project, a suggested computer-aided diagnosis (CAD) system for skin diseases divides skin conditions into six distinct categories. The noise and artifacts that were present in the images utilized in this experiment were eliminated by the use of several picture pre-processing methods. Image improvement strategies were used in order to further improve the overall image quality of the raw skin disease photographs. Experiments with a fundamental CNN model were done in order to evaluate its performance. A model called SkinNet-11 that uses Basis CNN as its fundamental base has been suggested. In order to test and enhance the robustness of the model, an ablation research is carried out on the network that we have suggested. The model was able to distinguish between different classes of skin diseases and accurately classify them. A testing and validation accuracy 98.00% were achieved with our proposed SkinNet-11 model when optimizer Adam was used in conjunction with a learning rate of 0.001. Our method may be of use to clinical professionals in the early stages of diagnosis and the formulation of treatment plans. In conclusion, the robust CNN(SkinNet-11) model used in this study demonstrated its potential in accurately detecting and classifying skin diseases.

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