Identification and Detection of Skin Cancer Using Deep Learning

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Data Analytics

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Identification and Detection of Skin Cancer Using Deep Learning

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Abstract

Among all types of cancer, skin cancer is the most serious and common.due to its complicated signs, skin cancer detection has been a challenge.skin cancer can be diagnosed sooner by studying abnormal skin changes.Since skin cancer cases are on the rise, it has a high mortality rate, and expensive healthcare treatments, it is essential to identify its abnormalities as soon as possible.different Deep Learning Neural Networks have found skin cancer.malignant and benign tumor images have comparable optics, making it challenging to achieve precise results.this technical report helps diagnose skin cancer automatically by classifying melanoma and benign images using deep learning models, minimizing mortality.skin lesion images are augmented and preprocessed to enhance the model's accuracy, and then the model's accuracy and loss are evaluated.this research uses the ResNet 50 neural network model, which outperforms past research article models with 98 % accuracy.

Keywords- Skin Cancer, Skin lession Images, ResNet50, Loss Function, Data Augmentation, Convolution Neural Network,Optimization

1 Introduction

Background and Motivation Skin cancer is hazardous.melanoma skin cancer is malignant. Its incidence has risen in the previous 30 years.according to the new number, 1 in 10 will get cancer(Filali et al.; 2022). Malignant "melanoma" and benign "non-melanoma" skin cancers can be differentiated.similarities between skin cancer lesions make classification difficult. Image processing tools help dermatologists spot this cancer early.dermatologists diagnose and assess skin cancer by combining microscopic (clinical) images captured with a digital camera or a mobile device with dermoscopic images made with a special camera that may show the pigment of the melanoma. Several computational tools assist dermatologists diagnose skin cancer. Computer-aided diagnostics helps dermatologists classify skin cancers. These devices can quickly detect skin cancer. Deep learning, clustering algorithms, and machine learning may assist diagnose skin lesions (Filali et al.; 2022).

The figures for skin cancer worldwide are also very concerning.according to recent studies, the number of new cancer cases diagnosed each year grew by 53% from 2008 to 2018 (Esteva et al.; 2017).The most common disease on the planet is thought to be skin cancer. In the United States, there are 5.4 million new cases of skin cancer each year (Siegel et al.; 2012). and the mortality rate is predicted to increase over the next decade.if skin cancer is discovered later on, the survival rate is less than 14% (Siegel et al.;

2012).detecting skin cancer early increases survival to 97% (Bray et al.; 2018).it has been discovered that a qualified dermatologist typically follows a set of stages, starting with a visual inspection of worrisome lesions, followed by dermoscopy and biopsy.this will take some time, and the patient's illness can worsen as a result.A successful diagnosis is also dependant on the clinician's skill and is therefore debatable.when diagnosing skin cancer, dermatologists with the most experience have an accuracy rate of less than 80%.(Marks; 2000) there are not enough qualified dermatologists available globally for public healthcare.the best indicator of a possible recovery is the early identification of cancer.A 10-year survival rate for cancer is produced by early diagnosis(Dubal et al.; 2017).recent advances in deep learning have improved skin cancer detection. Full examination and manual screening are traditional methods for detecting skin cancer.this technical report offers a comparison analysis to determine which skin cancer detection method is most effective.

1.1 Research Question

"In order to lower death rates, how accurately can early-stage skin cancer be identified utilizing deep learning algorithms and data augmentation methods? "

Without data augmentation, overfitting occurred.since one approach for increasing the dataset size is to use data augmentation.the dataset is made more diverse by this technique.from a single image, we may produce additional data.increasing the dataset size is mostly done to prevent overfitting.

1.2 Research Objectives And Contributions

Building an automatic deep learning model for early skin cancer detection is the purpose of this technical report.the Society for Imaging Informatics in Medicine (SIIM-ISIC) and the international Skin Imaging Collaboration have collected imaging data.this approach would benefit medical and healthcare workers and would target people of all ages, including both men and women.because this strategy would be affordable, smaller to larger hospitals might afford it.this study employs a variety of methods to achieve the goal set forth in the research question.it is divided into several components and objectives , each of which is explained below:

Chapter 2:Obj:Discussion of conventional and cutting-edge skin cancer research
Chapter 3:Obj:Outlines the methodology adopted in this research to identify skin cancer.
Chapter 4:Obj:Illustrates the Design Specification .
Chapter 5:Obj:Demonstrates how the ResNet 50 architecture has been implemented.
Chapter 6:Obj:Illustration of the model training parameters.
Chapter 7:Obj:Evaluation of the model's results after implementation.
Chapter 8:Obj:Conclusion of the technical report.

2 Related Work

2.1 Conventional Methods

To bridge the existing gaps among a patient and a cancer specialist, this research proposes a revolutionary cloud-based solution that works together with deep learning analysis to assess the cancer employing Deep Convolution Neural Network (Gaur et al.; 2022).framework for coordinating deep learning analyses with cloud services is presented. (Gaur et al.; 2022) presented for the purpose of pixel-by-pixel processing of picture samples, deep convolutional neural networks selected since they have highly precise ,accuracy values and well-organized, arranged architecture (Gaur et al.; 2022). The results show that the model was excellent at detecting the cancer,with an accuracy of 76.1% (Gaur et al.; 2022).The process of "data augmentation" can increase the variety of the datasets used to train machine learning algorithms.the author (Guergueb and Akhloufi; 2021) used a translation of -10, rotations between -5 and +5, and a 1 degree increment for each rotation (Guergueb and Akhloufi; 2021).A set of much more than 36,000 photos from various databases were used in the studies (Guergueb and Akhloufi; 2021).A study was done to evaluate deep learning models for skin lesion (Guergueb and Akhloufi; 2021).the models were trained and tested on a brand-new, big dataset that was produced by combining various open-source datasets.the study compared 20 different DL models in total (Guergueb and Akhloufi; 2021).according to the statistics,EfficientnetB7 performs better than all other models and has a 99.1% accuracy rate (Guergueb and Akhloufi; 2021).

In 2022 (Fraiwan and Faouri; 2022) research focuses on the effectiveness of raw deep transfer learning for classifying images of skin lesions across seven distinct categories.a system that employs the HAM1000 dataset of dermoscopy images as input requiring feature extraction or preprocessing was developed using thirteen deep transfer learning models (Fraiwan and Faouri; 2022).evaluation was used to determine this method's advantages and disadvantages (Fraiwan and Faouri; 2022).deep learning artificial intelligence is widely credited with the recent improvements in image-based diagnostics (Fraiwan and Faouri; 2022). Skin cancer can be prevented by a number of antioxidants, such as those present in foods such the vitamins C, E, and A, zinc, and selenium (Padmaja et al.; 2022).the "Deep Learning" (DL) approach can be used to detect cancerous tumors. The study's objective was to gain a deeper understanding of how big data networks can help medical professionals detect skin cancer more quickly.The accuracy, sensitivity, and specificity of "Convolutional Neural Network" for deep learning in the early detection of skin cancer have been examined statistically using IBM SPSS software (Padmaja et al.; 2022).

This study (Hosny et al.; 2018) suggests an automated system for classifying skin lesions (Hosny et al.; 2018).this method applies transfer learning to Alex Net coupled by fine-tuning and data augmentation, and employs a deep learning network which has been trained to categorize three different lesions (Hosny et al.; 2018).the proposed model is trained and evaluated using the ph2 dataset(Hosny et al.; 2018).medical and healthcare professionals are concerned about the rise in instances of melanoma and non melanoma skin cancer.according to figures compiled by the World Health Organization,the number of skin cancer cases has substantially increased in recent years (Didona et al.; 2018).statistics show that more than 1.3 billion people worldwide have melanomas and more than 2 million people have non-melanoma skin cancer (Didona et al.; 2018).a thorough literature evaluation of the current methods for skin cancer detection is conducted by the authors of (Jana et al.; 2017).Among all skin cancer detection methods,SVM and Ad boost yield the best results. This article discusses the use of SVM for the classification of skin cancer images as well as a survey and analysis of the various ANN architectures, accuracy results, and performance. It is simply explained how melanoma works and how to detect it.

This knowledge is useful for separating healthy and cancerous skin cells (Jana et al.; 2017).a novel Three-Way Decision (TWD) theory-based uncertainty quantification model was presented by (Abdar et al.; 2021), and it was utilized to analyze two picture datasets. (Abdar et al.; 2021) work aimed to evaluate the efficacy of risk quantification models utilizing Bayesian CNNs and TWD to increase the effectiveness of computer-aided diagnostic systems, rather than to offer a brand-new, state-of-the-art deep learning model (Abdar et al.; 2021). 88.95 percent of the first dataset's accuracy and 90.96 percent of the second dataset's accuracy were accurate (Abdar et al.; 2021).Skin cancer, which can be fatal, is one of the top three tumors caused by DNA damage. This damaged DNA causes unchecked cell proliferation, and the issue is presently becoming scarier very rapidly (Ali et al.; 2021).in this research,the proposed DCNN model outperforms in terms of classification accuracy than other transfer learning methods.The proposed approach can differentiate between benign and cancerous skin lesions (Ali et al.; 2021).

In (Alfed et al.; 2015) A pigment system approach for detecting skin cancer is suggested.The proposed technique extracts statistical data from the pigment network image using already existing tools for pigment network extraction (Alfed et al.; 2015).after that, the features were used to train a neural network classifier.The recommended method was tested on a collection of tagged dermoscopy images, and the results show that it has an extremely low error recognition rate and high predictive accuracy (Alfed et al.; 2015).This article presents the method for melanoma skin cancer detection (Kamboj et al.; 2018).initially, a number of cleaning and classification techniques were utilized to improve the image and segregate the focus area. A number of attributes were extracted using the HSV and YCbCr color spaces (Kamboj et al.; 2018).the feature performance of three alternative classifier types—Naive Bayes, Decision Trees, and KNN classifiers—is assessed (Kamboj et al.; 2018).the Decision Tree classifier, on the other hand, is found to outperform than the other models, obtaining an accuracy of 82.35% (Kamboj et al.; 2018).
Asymmetry, harsh edge, compressed index, fourier transform, color change, length, and border inconsistency are examples of characteristics of the cancer image that are routinely considered and evaluated while analyzing patients with skin cancer (Bumrungkun et al.; 2018).Picture segmentation is used in the automatic skin cancer diagnosis method to extract and analyze these aspects. A method for segmenting images using Support Vector Machines and is proposed by (Bumrungkun et al.; 2018). SVM helps snake active contour discover the appropriate parameters for the snake technique (Bumrungkun et al.; 2018). It was the goal of the authors of (Nezhadian and Rashidi; 2017) to distinguish between benign and malignant melanoma. The most crucial step is the accurate segmentation of the image. The initial area was specified by the user, and an active counter model was utilized to improve accuracy. RGB elements and texture-based features were combined to derive picture features. For wavelet transform approximation matrices, TC features were shown to be the most useful feature (Nezhadian and Rashidi; 2017).

In comparison to many existing methods, Genetic Programming (GP), a unique evolutionary computational paradigm, offers the potential to produce answers for picture categorization challenges. (Ain et al.; 2017) A algorithm for the rapid recognition of skin cancer was constructed in this article using GP as a feature selection technique (Ain et al.; 2017).The results revealed that GP significantly excelled or produced results similar to those of the skin cancer detection techniques now in use (Ain et al.; 2017).a hybrid technique is offered by for examining any suspicious lesions and identifying melanoma skin cancer(Daghrir et al.; 2020). The proposed system depends on three different forecasts: Two common machine learning techniques, a convolutional neural network, and a set of variables used to define the contours, form, and color of a skin lesion were taught(Daghrir et al.; 2020). Then, to improve their performances, these strategies are combined using a majority vote. The trials' findings show that combining the three procedures yields the highest level of accuracy (Daghrir et al.; 2020).

Researchers from (Tan et al.; 2019) suggested an intelligent decision-support technique for detecting skin cancer. Because constructing a successful lesion representation is crucial to the success of lesion classification, the discriminative capacity of many different types of features is exploited (Tan et al.; 2019). An on-device inference technique was presented in a recent work (Dai et al.; 2019). and offers a number of advantages over cloud-based alternatives. These include lowered prices, enhanced security, more accessibility, and lower prices (Dai et al.; 2019).

2.1.1 ResNet Deep Learning Models

Biomedical datasets are produced for this (Demir et al.; 2019) study by entering patient data onto computers. By categorizing the images in their dataset as benign or malignant, researchers hope to create a practical technique for skin cancer earlier detection.2437 training images, 660 test images, and 200 validation images make up their dataset(Demir et al.; 2019). for the classification challenge, deep learning architectures ResNet-101 and Inception-v3 are employed (Demir et al.; 2019).when the obtained findings are reviewed, the ResNet-101 architecture achieves an accuracy rate of 84.09%, while the Inception-v3 architecture achieves an accuracy rate of 87.42%.(Demir et al.; 2019) .in study (Abd ElGhany et al.; 2021) looked into how well deep learning could classify seven different primary skin lesions.

On a total of 12519 HAM dermoscopic pictures, performance evaluation using the pretrained ResNet50 network surpasses other robust networks(Abd ElGhany et al.; 2021). The effectiveness of several fine-tuning methods, including regularization, batch normalization, and hyperparameter optimization, has been examined. With the best parameters, Adam optimizer and cross-entropy loss function are also used. For evaluation, the created deep model contrasted two potent models, namely InceptionV3 and VGG16 (Abd ElGhany et al.; 2021). The suggested fine-tuned deep learning model demonstrates that ne-tuning networks are more accurate at diagnosing problems than other potent methods (Abd ElGhany et al.; 2021).despite the fact that the dataset used is rather imbalanced, the model produced encouraging results. These models are simple to use and can help dermatologists (Abd ElGhany et al.; 2021).CNN was (Gouda et al.; 2022) utilized to detect malignant and benign tumors in the ISIC2018 dataset. 3533 benign, malignant, nonmelanocytic, and melanocytic skin lesions are included (Gouda et al.;

2022).ESRGAN edited and enhanced the images.preprocessing included enhancing, normalizing, and resizing the photographs.CNN can classify skin lesion photographs using repeated results.fine-tuning was done with Resnet50, InceptionV3, and Inception Resnet. (Gouda et al.; 2022) Creativity and contribution of this research include the usage of ESRGAN as a preprocessing phase. Our created model matched the pretrained model.the suggested technique worked in simulations using the ISIC 2018 skin lesion dataset. CNN obtained 83.2% accuracy, compared to Resnet50 (83.7%), InceptionV3 (85.8%), and Inception Resnet (84%) (Gouda et al.; 2022).
Chapter 2's goal (in Section 1.3) has been met, partially resolving the research question (1.2). The method for detecting skin cancer is discussed in the following section

Research Article	Model Name	Year	Dataset	Accuracy
Demir et al. (2019)	Inception v3-ResNet50	2019	ISIC	0.84
Abd ElGhany et al. (2021)	VGG16-Resnet50	2021	HAM1000	0.99
Gaur et al. (2022)	Mobile net v2	2022	SIIM-ISIC	0.77
Gouda et al. (2022)	Inception -ResNet50	2020	HAM1000	0.83
Daghrir et al. (2020)	VGG16	2020	ISIC2018	0.85
Kamboj et al. (2018)	KNN classifier	2018	HAAM1000	0.82
Abdar et al. (2021)	TWD	2021	HAM1000	0.90
Fraiwan and Faouri (2022)	Transfer Learning	2022	HAM1000	0.92

Table 1: an overview of related work

3 Methodology

This technical paper adopts a modified technique using a Knowledge Discovery-based framework (KDD). The primary objective of this research is to identify skin cancer using an automated model that was created using data which is publicly available and the link has been mention in data collection section.The process flow diagram for answering our research question is shown in Figure 1.It includes several steps, including data collecting, exploratory analysis, data preprocessing,feature extraction, modelling, detection of skin cancer lesions, and evaluation

3.1 Data Collection

The dataset [1] selected for the study is based on publicly accessible skin lesion images of benign and malignant categories from the International Skin Imaging Collaboration (ISIC) Archive database.The International Skin Imaging Collaboration created the dataset.The collection consists of images in two different image formats, including JPEG and the medical imaging format DICOM.While JPEG images come in a variety of sizes, the DICOM image format has a fixed dimension of 1024*1024.Figure 3 depicts the benign group, while Figure 2 displays several images of melanoma skin lesions.with 98% benign instances and only 2% malignant cases, the dataset is greatly unbalanced. The dataset has several records for an individual patient, it was discovered after careful examination. For the benign class, some patients have even more than 250 photos.The dataset is therefore biased in favor of the benign class. In comparison to the benign class, there are less

[1]https://www.kaggle.com/competitions/siim-isic-melanoma-classification/data

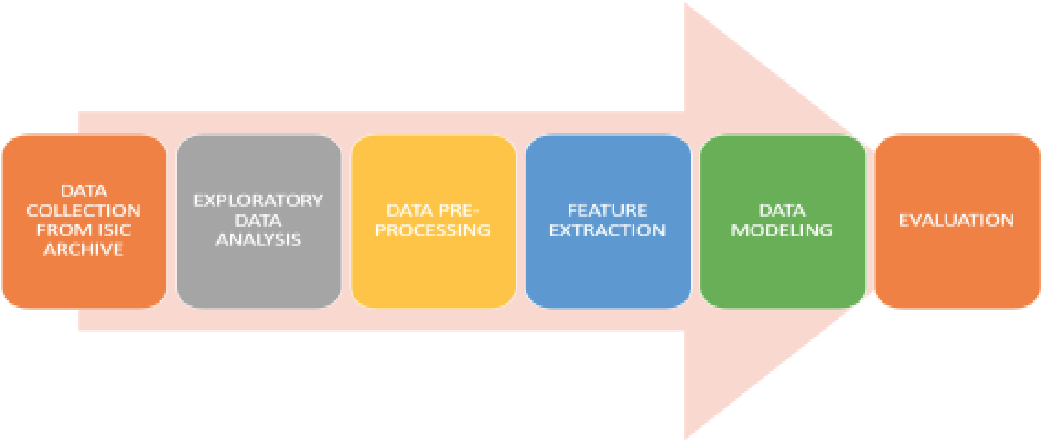

Figure 1: Skin Cancer Detection Design Methodology

malignant pictures. The benign category was compressed to equalize it to the number of malignant cases in order for the model to function properly.The malignant cases, with a count of 584, were taken as the minority class. A total of 1,168 different photographs were taken into consideration for the project. The skin lesions are malignant when they are irregular, have uneven borders, have two shades, etc.However, the benign are uniform, one color, and have borders that resemble little moles.

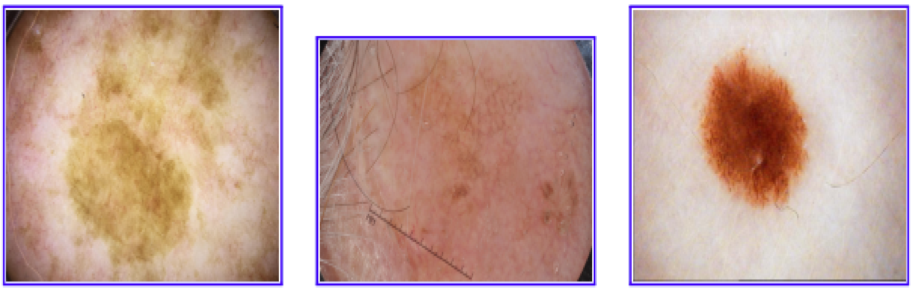

Figure 2: : Melanoma Skin Lesion Images

3.2 Exploratory Data Analysis

Exploratory data analysis was done to better grasp the information and the metadata that was associated with it.numerous discoveries made during the investigation were crucial in processing the pictures.Figure 4 demonstrates that men are more vulnerable to melanoma than females are, according to the dataset's male to female ratio of benign and malignant instances. There were six separate body areas where the malignancy was found, including the body, head/neck, lower extremities, upper limbs, palm/sole, and oral-genital region. Figure 5 illustrates major bodily sections, with the chest, lower extremities, and upper extremities showing the greatest prevalence of cancer. Less cancer is found in the head, neck, and reproductive organs Atypical melanocytic proliferation,

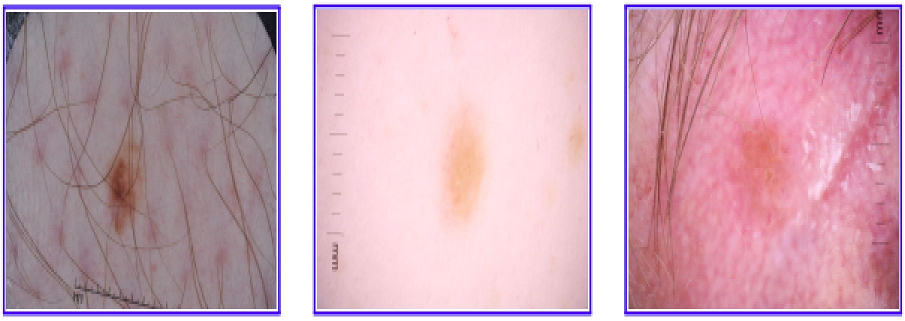

Figure 3: Benign Skin Lesion Images

seborrheic keratosis, lesion NOS, lichenoid keratosis, solar lentigo, and unknown cancer account for the remaining 1 percentage of cases, as illustrated in figure 5. The majority of cases fall into the unknown cancer group, which accounts for 81 % of the entire dataset.

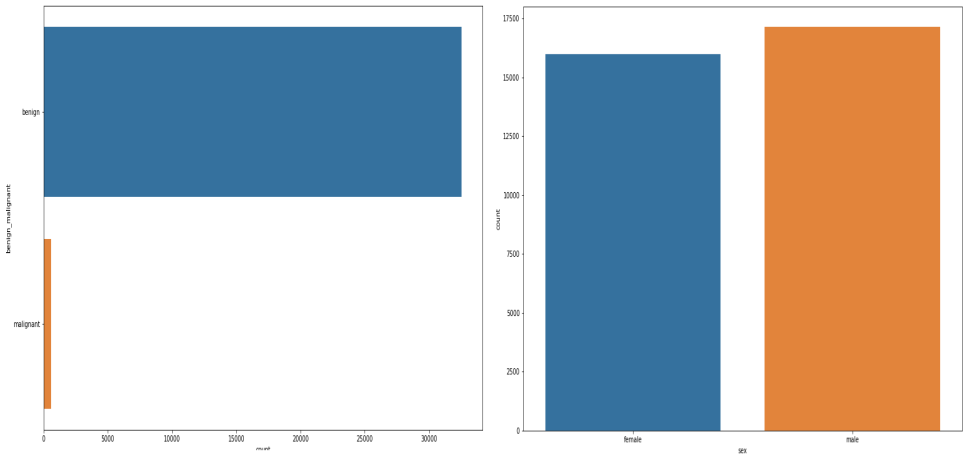

Figure 4: Benign And Malignant Skin Lession Images Ratio According To Sex Ratio

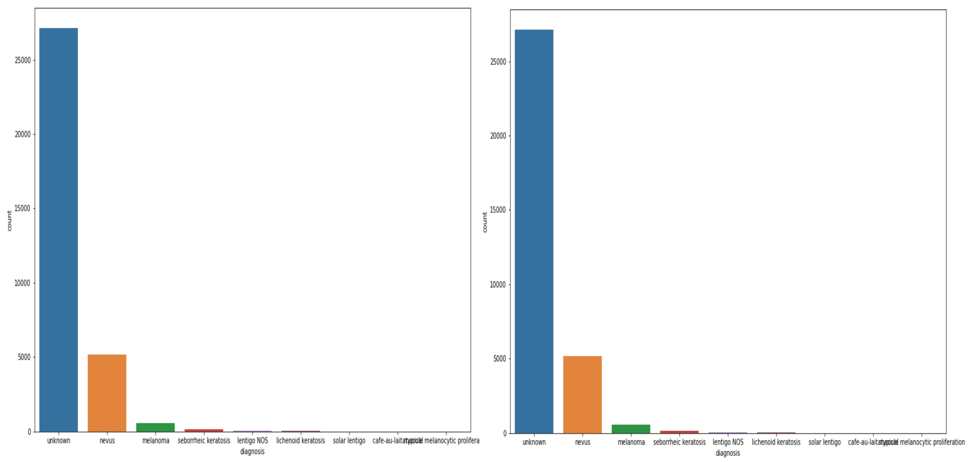

Figure 5: Different Types of Skin Cancer According To Body Parts

3.3 Data Pre-Processing

3.3.1 Data conversion and loading

Images that are cancerous and benign are used in this research.A balanced mixture of benign and malignant skin lesions are represented in this dataset. The size of each image in this dataset is 224x224x3. The dataset's images of skin cancer fall into two categories: Malignant and benign moles on the skin ,all the dataset images are in jpeg format.

3.3.2 Data Splitting

The ISIC Melanoma classification Dataset was divided in Validation and Training datasets in an 80/20 ratio since it only includes Train and Test Data.

3.3.3 Data augmentation

Upgraded images with related masks for orientation, reflections, shifting, brightness, and resizing were created for each image in the dataset. The low quality of the raw lesion images produced by electronic detectors limits detection and evaluation. There were 3213 photos in the test folder and 15104 altogether, including benign and cancerous images. Oversampling was used on the ominous images to resolve the uneven distribution of classes.

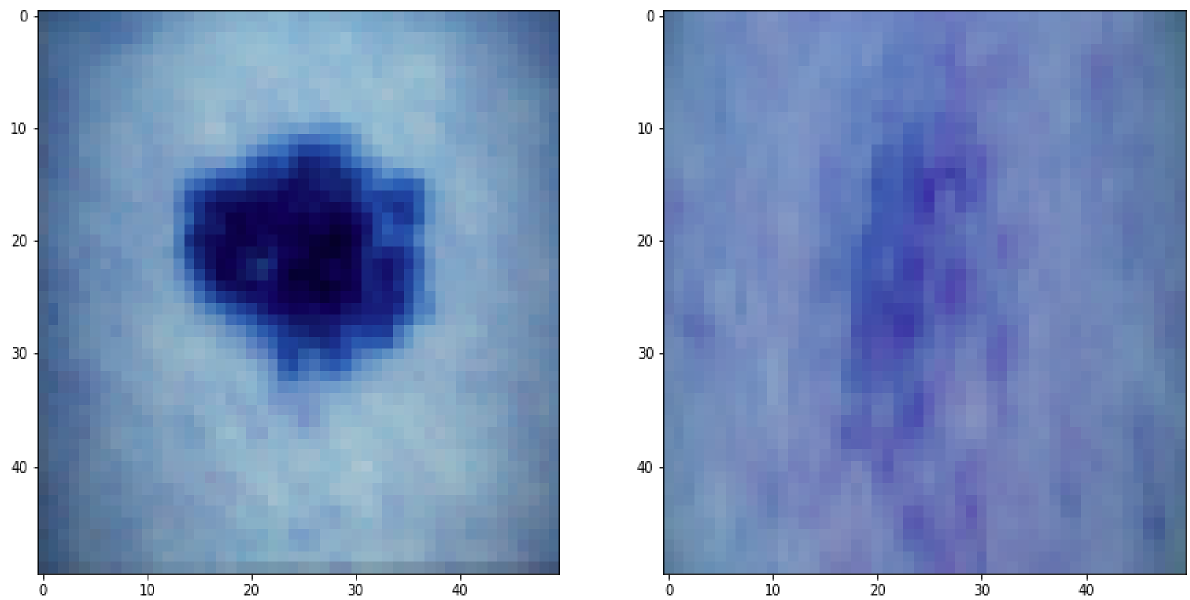

Figure 6: Data Augmentation

3.4 Feature Extraction

The Principles of Image Classification identify object forms and geometry. It includes picture normalization, segmentation, key feature extraction, and class identification. CNN architecture changed this domain by grasping basic shapes and geometric in the first layer, then understanding images features inside the deeper layers, resulting in more exact image classification. CNN handles feature extraction and model training for this research.

3.5 Modelling

Skin cancer detection uses many object detection techniques and models. Deep learning models operate better than standard methods for image classification, according to related research. This research uses ResNet50 to identify skin cancer.

3.6 Evaluation

The metrics of accuracy and loss are used to evaluate the models that do binary classification. To improve the models' outputs, Adam optimization is used to the model. Results are shown in graphs of epoch against accuracy and epoch against loss fulfilled the goal of chapter 3 (in 1.3), which again only partially addresses the research question (1.2). The design specification flow for skin cancer detection is shown in the following section.

4 Design Specification

Conventional skin cancer detection approaches in skin lesion images concentrated more on extracting various lesion traits to produce precise predictions, as detailed in the associated paper. These techniques, nevertheless, were expensive, necessitated outside assistance, and produced a large number of incorrect predictions.

Deep learning techniques, on the other hand, have recently been quite effective in solving image separation and classification issues without the need for human participation. The deep learning algorithms have been shown to extract features skin lesion features, displaying superior performance than the older methods, for the specific situation of segmenting skin lesion photos to detect skin cancer. As a result, the deep learning approach for image segmentation has been used in this study, in which each pixel in the skin lesion image is categorized frame by frame. The model was developed using the cutting-edge ResNet50 model architecture, as suggested by(Singh et al.; 2022). Figure displays the research's overall layout.

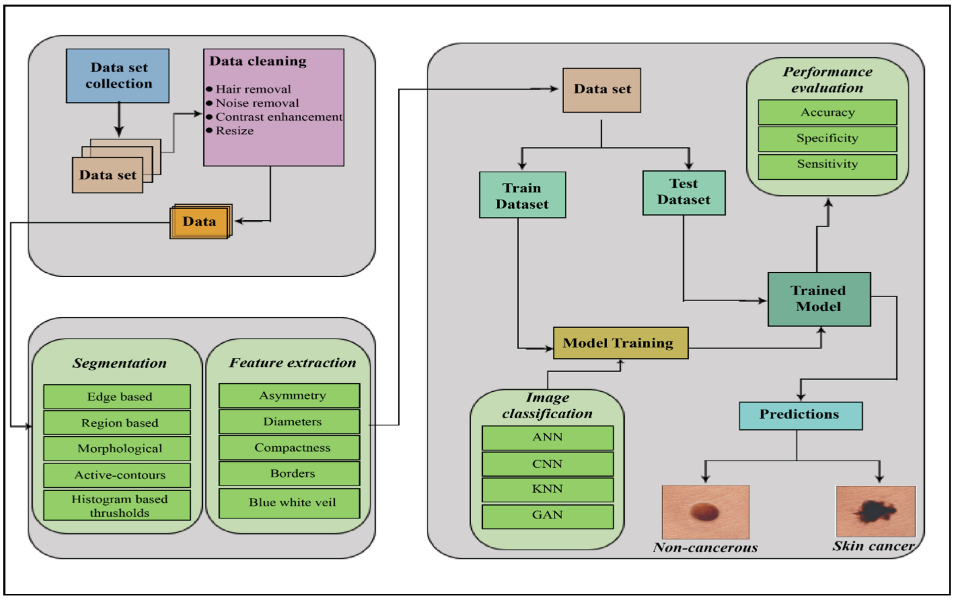

Figure 7: Design Flow For Detecting Skin Cancer
source (Dildar et al.; 2021)

5 Model Implementation For Skin Cancer Detection

The technologies utilized to carry out the research are covered in this part, along with implementation specifics.an execution of model is build in python,with jupyter noteboook. Additionally, Google Collaboratory, a free cloud-based platform for machine learning development, is used for code. Anaconda is an open and free platform where Python and R programming can be used to perform tasks like huge data processing, predictive modeling, data mining, etc. It is a favored platform since it manages all library dependencies and management. Another open-source web tool, Jupyter Notebook, allows for the creation and sharing of documents that contain live code, graphics, data processing, and other elements. MatplotLib, a Python visualization toolkit, was used to plot the diagrams for data exploration and the evaluation matrix. As a backend, Keras is utilized. In fact, Keras is an API made for people, not machines. Since deep learning methods require that functions like feature extraction be performed individually, but with Keras, the extracted features is handled on its own,for the research Keras for generating the models.On base of Tensor Flow architecture, it is constructed.

5.1 Implementation using Model ResNet50

ResNet50 is selected as a model for this research due to its composite structures Residual Machine Learning models are also referred to as ResNet models.ResNet-50 is a 50-layer convolutional neural network.the approach was developed to address the issue of sophisticated deep neural networks that tend to overfit as additional layers or attributes are added. The outputs of the layers that are stacked together are added to the connections' outputs, which carry out identity mapping. This fixes two issues by making the procedure simple to optimize and increasing accuracy as the model's depth increases without producing excessive overfitting (Singh et al.; 2022).

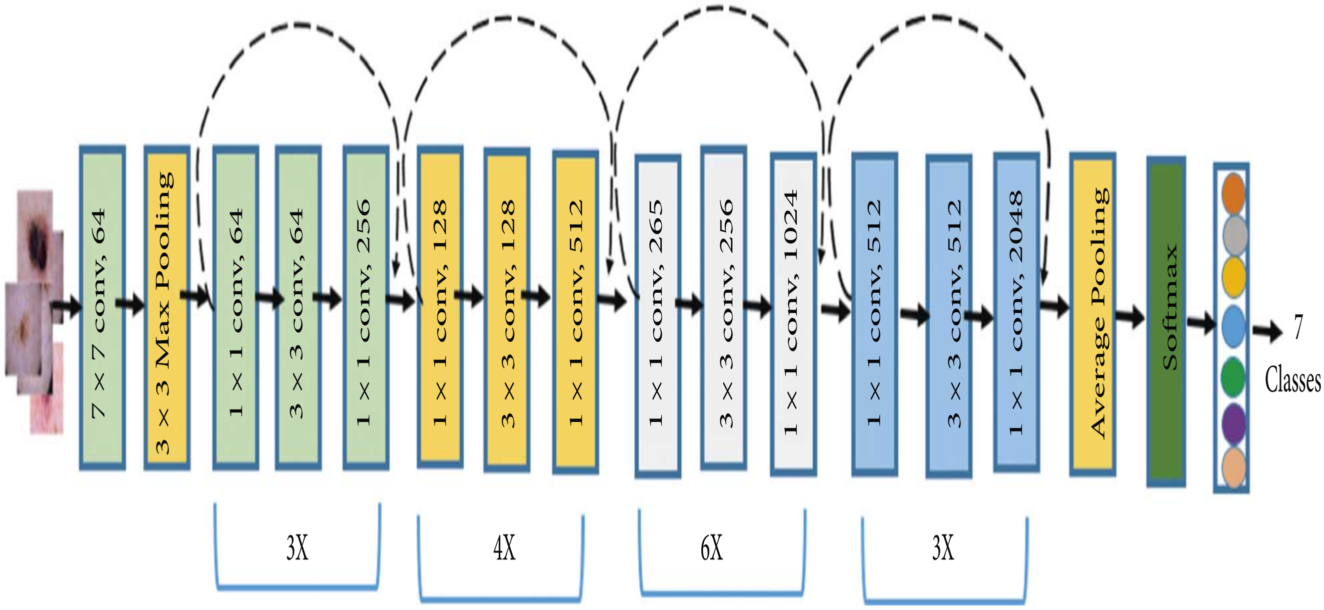

Figure 8: ResNet 50 Architecture For Skin Cancer Detection
source (Abd ElGhany et al.; 2021)

Figure 8 depicts the connections between each of ResNet50's 50 layers. As seen in the above image, ResNet50's design is divided into 4 stages. The system can accept an image with a size that is multiples of 32 and a channel length of 3. We will assume the filter size is 224 by 224 by 3 for the sake of clarity (Hasan et al.; 2021). each ResNet design uses 77 percent and 33 percent kernel sizes, respectively, for initial convolution and maximum pooling. The first stage of the network then starts, consisting of three residual blocks, each containing all three layers. The kernels used to carry out the convolution process are then 64, 64, and 128 in size for each of the three levels of stage 1's unit.The same link is indicated by the curved arrow. Stride two is utilized for convolution in the dense block, generating a 1/2 input in terms of height and width but twice the channel width, as seen by the dotted connection arrows. The bottom layer of the system is the average pooling layer. The next layer has a thousand completely connected neurons. Images of both malignant and benign cancer are included of our dataset (Hasan et al.; 2021). (Abd ElGhany et al.; 2021)As shown in the figure below, the ResNet50 has an extra identity mapping. Let H stand for the mapping you want (x) (Abd ElGhany et al.; 2021). The layers are arranged in this way: F(x) = H(x) x. If the original mapping is changed into F(x) + x, it can be easier to optimize the residual mapping than the original, unreferenced mapping. In optimal identity mapping, the residual can be pushed to zero more than fitting the identity mapping to nonlinear layers (Abd ElGhany et al.; 2021).

ReLU: Hidden layers are ReLu-activated (Abd ElGhany et al.; 2021). After Max pooling layers came three linked layers. Last-layer dropout and SoftMax classifier are coupled for good training accuracy. SoftMax smooths and connects dropout findings.(Abd ElGhany et al.; 2021)feature mapping uses convolutions, ReLU, and batch normalization. For a bounded feature map, the model is partitioned into blocks with stacked layers. The model prepared 100 dataset epochs (Abd ElGhany et al.; 2021).ReLU is the most frequent mul-

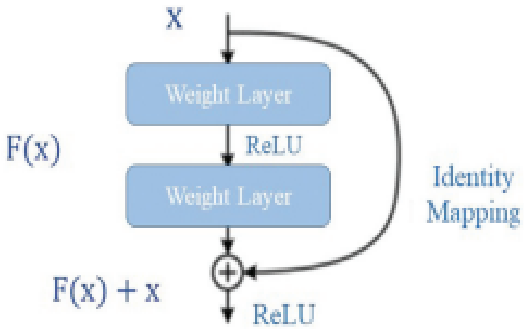

Figure 9: The residual identity mapping
source (Abd ElGhany et al.; 2021)

tilayer activation function. ReLU solves vanishing gradient problems (Abd ElGhany et al.; 2021).

7×7 kernel Convolution Operation: This model's convolution operation takes two inputs: 1. An image with a dimension of 128*128*3 and a channel count of 3. 2. 16 filters, or feature extractors of size 3*3, are also used. The relationship between a convolution block's input and output is seen in the formula below:

$$x(output) = \left| \frac{x(input) + 2p - k}{s} \right| + 1 \tag{1}$$

where p is the padding size, s is the stride size, and k is the number of filters. The x(input), which is 128*128*3 in our ResNet design, is changed to 128*128*16 after passing through two convolution layers, as can be seen in the first layer. The symbol 2@Conv in the figure indicates that the network is using two consecutive convolution layers. The output tensors of the convolution procedures are c1, c2, and others

Max Pooling Operation: Max pooling shrinks feature maps. This is done to precisely represent the image's context while maintaining only its important features. This method requires the filter size and stride length. This study's ResNet model has a 2*2 filter and a 2 stride. p1, p2, and others are the max pooling findings in this study's ResNet architecture. Figure 9 depicts max pooling.

Figure 10: Max Pooling Operation using stride 2 and a 2x2 filter

Dropout Layer: Dropout layers are crucial for preventing the overfitting problem and reducing the deep neural network's training time. Our model includes the dropout layer it after every max pooling operation.

SoftMax: SoftMax maximizes the target classes' logit values to map classes to logits. It can also produce class probabilities. This can contribute to an effective machine-learning model and effective training. SoftMax is beneficial for network model optimization and normalization. SoftMax squashes (0, 1) vectors so they add to 1 These vectors are multiclassification scores.

Skip connections: In order to skip some network tiers and transport a layer's output directly to the network's final layers, we employed skip connections in the model design. By utilizing skip connections in the ResNet architecture, it is possible to immediately employ the taught features from the network's coder component in the processor part to up-sample the skin lesion image.

The goal of chapter 4 (in paragraph 1.3) has been met, which again only substantially addresses the research question (1.2). The Model Training for Skin Cancer Detection is explained in the following section.

6 Model Training

The Adam Optimizer was used to create the ResNet50 model since it performed better than the other optimizers. We have had the binary cross entropy loss function in the model because each pixel in the skin lesion image has the potential to be either benign or malignant. Keras callbacks were also used to train the model in addition to that. The Early Stopping tolerance was set to 30, and if the validation loss did not decrease for 20 consecutive epochs, the program would terminate. If the validation loss did not decrease for five consecutive epochs, it was configured so that the learning rate would decrease by a factor of 0.1. The learning rate's minimum value was set at 1e-12. A batch size of 128 was utilized to fit the model over a period of 20 epoch.

Chapter 6's goal (in Section 1.3) has been accomplished, partially resolving the research question (1.2). The Model Evaluation and Results are shown in the following section

7 Model Evaluation

The ResNet50 model was trained over 20 epochs and a batch size of 128. Each epoch consisted of 63 steps.as can be seen in below figure loss function and accuracy improved after each epochs.

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

filepath="weights.hdf5"
checkpoint = ModelCheckpoint(filepath, monitor='loss', verbose=1, save_best_only=True, mode='min')
history=model.fit(x_train,y_train,batch_size=128,epochs=20,verbose=1,validation_split=0.33,callbacks=[checkpoint])

Epoch 1/20
63/63 [==============================] - ETA: 0s - loss: 0.2178 - accuracy: 0.9705
Epoch 1: loss improved from inf to 0.21780, saving model to weights.hdf5
63/63 [==============================] - 162s 3s/step - loss: 0.2178 - accuracy: 0.9705 - val_loss: 0.0951 - val_accuracy: 0.9813
Epoch 2/20
63/63 [==============================] - ETA: 0s - loss: 0.0912 - accuracy: 0.9821
Epoch 2: loss improved from 0.21780 to 0.09116, saving model to weights.hdf5
63/63 [==============================] - 150s 2s/step - loss: 0.0912 - accuracy: 0.9821 - val_loss: 0.0931 - val_accuracy: 0.9813
Epoch 3/20
63/63 [==============================] - ETA: 0s - loss: 0.0919 - accuracy: 0.9821
Epoch 3: loss did not improve from 0.09116
63/63 [==============================] - 149s 2s/step - loss: 0.0919 - accuracy: 0.9821 - val_loss: 0.0933 - val_accuracy: 0.9813
Epoch 4/20
63/63 [==============================] - ETA: 0s - loss: 0.0922 - accuracy: 0.9821
Epoch 4: loss did not improve from 0.09116
63/63 [==============================] - 149s 2s/step - loss: 0.0922 - accuracy: 0.9821 - val_loss: 0.0931 - val_accuracy: 0.9813
Epoch 5/20
63/63 [==============================] - ETA: 0s - loss: 0.0907 - accuracy: 0.9821
Epoch 5: loss improved from 0.09116 to 0.09069, saving model to weights.hdf5
63/63 [==============================] - 155s 2s/step - loss: 0.0907 - accuracy: 0.9821 - val_loss: 0.0931 - val_accuracy: 0.9813
Epoch 6/20
63/63 [==============================] - ETA: 0s - loss: 0.0923 - accuracy: 0.9821
Epoch 6: loss did not improve from 0.09069
63/63 [==============================] - 149s 2s/step - loss: 0.0923 - accuracy: 0.9821 - val_loss: 0.0931 - val_accuracy: 0.9813
Epoch 7/20
63/63 [==============================] - ETA: 0s - loss: 0.0930 - accuracy: 0.9821
Epoch 7: loss did not improve from 0.09069
63/63 [==============================] - 147s 2s/step - loss: 0.0930 - accuracy: 0.9821 - val_loss: 0.0982 - val_accuracy: 0.9813
Epoch 8/20
63/63 [==============================] - ETA: 0s - loss: 0.0920 - accuracy: 0.9821
Epoch 8: loss did not improve from 0.09069
63/63 [==============================] - 149s 2s/step - loss: 0.0920 - accuracy: 0.9821 - val_loss: 0.0936 - val_accuracy: 0.9813
Epoch 9/20
63/63 [==============================] - 154s 2s/step - loss: 0.0915 - accuracy: 0.9821 - val_loss: 0.0930 - val_accuracy: 0.9813
```

Figure 11: Skin Cancer Detection Model Training

7.1 Evaluation Metrics:

Various model evaluation measures were used to assess the ResNet50 model's ability to identify skin cancer. These metrics aid in assessing the model's efficacy in precisely identifying skin cancer using skin lesions..

7.1.1 Accuracy:

Accuracy was a second evaluation parameter that the model utilized to assess performance. The ratio of the model's total number of predictions to its true predictions is known as the accuracy of the model. In past studies, including that of(Singh et al.; 2022), accuracy evaluation metrics were employed to assess how well the ResNet 50 model could identify skin cancer. Figure displays a graph of accuracy as a function of epochs. For the training dataset, the model attained a fantastic accuracy of about 98 %.

7.1.2 Model Loss:

Figure illustrates how well the model's loss curves behave, indicating that the model was well trained. The graph, however, held steady as the number of epochs increased, indicating that the model was not overfit. Furthermore, the curve's slow decline showed that good convergence had occurred.

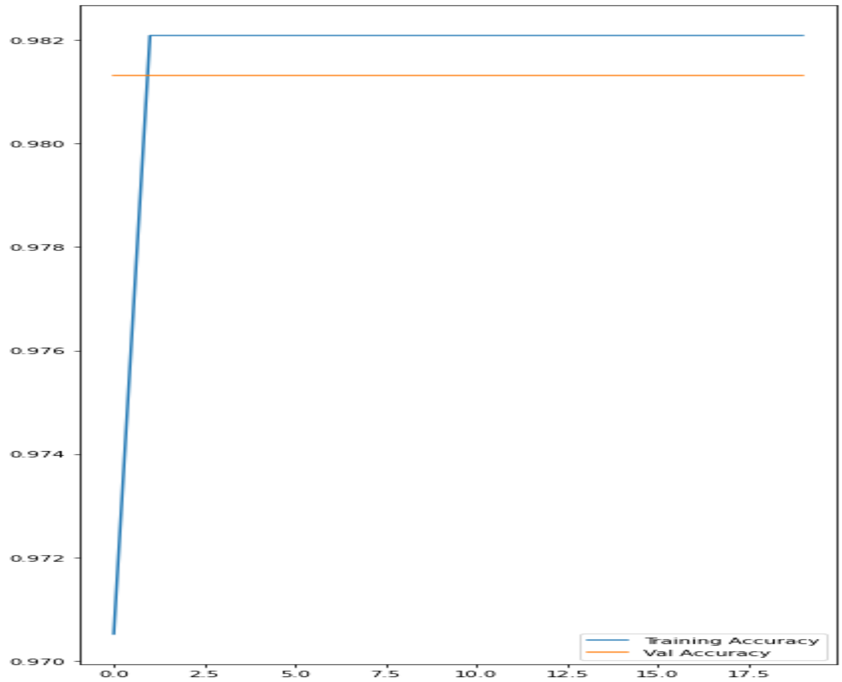

Figure 12: Accuracy against Number of Epochs

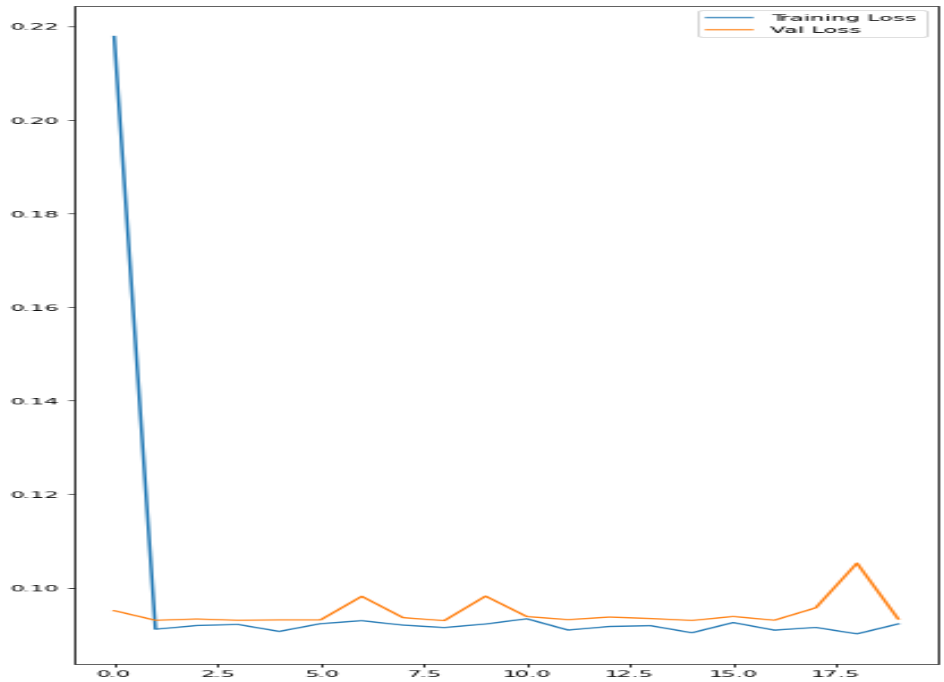

Figure 13: Loss against Number of Epochs

7.2 Model Parameters:

7.2.1 Accuracy Loss Function

The model was ran using the "Weighted Cross Entropy" and "Categorical Cross Entropy" loss functions. The datasets with similarly scattered data across classes are the best for categorical cross entropy. On the other hand, Weighted Cross Entropy outperforms when the dataset's data is unbalanced. The Categorical Cross Entropy outperforms in the accuracy evaluation measure, as seen in Table 2, hence it is used to construct the final model.

Epoch	Categorical CE-Train	Categorical CE-Valid	Weighted CE-Train	Weighted CE-Valid
1	0.9705	0.9813	0.9407	0.9613
5	0.9820	0.9812	0.9513	0.9618
10	0.9821	0.9812	0.9513	0.9619
15	0.9821	0.9813	0.9621	0.9619
20	0.9821	0.9813	0.9634	0.9620

Table 2: Comparison of Accuracy for Categorical and Weighted Cross Entropy

7.2.2 Optimizer

In this study, a variety of optimizers were tried to determine which one would best solve the overfitting problem. The model needs optimizers to speed up the loss minimization procedure. The procedure entails initializing the bias and weights, choosing the best values for the learning algorithm and some other parameters, and then correcting the bias. While building the model, we employed a variety of optimizers, including Adam, Adamax, and SGD optimizer, and we evaluated the accuracy of each optimizer as the number of epochs increased. The Adam optimizer is the most efficient when accuracy of several optimizers is compared in Table 3.

Epoch	Adam Optimizer	Adamax Optimizer	SGD Optimizer	Nadam Optimizer
1	0.9705	0.9423	0.9430	0.9508
5	0.9820	0.9445	0.9456	0.9508
10	0.9821	0.9512	0.9460	0.9511
15	0.9821	0.9512	0.9501	0.9523
20	0.9821	0.9547	0.9506	0.9591

Table 3: Comparison of accuracy for several optimizers

7.3 Discussion:

For the purpose of the study, the ISIC dataset was used to construct a deep learning model for the detection of skin cancer. The model that was used was ResNet50, and the model achieved a level of accuracy of 98.53%. Several different kinds of optimizer were used for the purpose of improving the performance of the model; however, the adam optimizer was the most effective of the bunch. From the figure below, we can see a comparison of previous research work with our proposed model, and it is clearly evident that the ResNet50 model that was used for this research outperforms all recent work model, in terms of better accuracy, the number of skin lesion images that were used for the model implementation, and also the fact that the loss function and loss accuracy are efficient compared to other models. This model had a total of fifty layers when it was finished.

Author	Accuracy (%)	Total Images used	Models Used
(Abd ElGhany et al.;2021)	96	10015	ResNet50,VGG16
(Demir et al.;2019)	84.09	3297	Inception-v3,ResNet50
(Gouda et al.;2022)	83.7	3533	Inception ResNet,ResNet50
(Gaur et al.; 2022)	77.61	3297	Mobile net v2
Proposed model	98.53	15314	ResNet50

Figure 14: Table 4:Comparison With Previous Research

The goal of chapter 7 (in 1.3) has been achieved, and it fully answers to the research question (1.2). The research is concluded with results in the next section.

8 Conclusion

The research question for this study, which was the detection of skin cancer using deep learning and data augmentation methods, has been satisfactorily answered. Additionally, in the section of the study devoted to model implementation and evaluation, all of the objectives have been met and the study has been finished. In the past, many researchers have developed many different models to predict cancer at the earliest stage.early detection of skin cancer has been shown to lower the overall mortality rate, and this automatic detection model has the potential to contribute positively toward achieving that goal. The problems that arose when attempting to classify skin lesions as cancerous or benign have been resolved, and the results can be seen under the section on data augmentation.an accurate diagnosis of the specific type of cancer at the appropriate time can help save the lives of many people. As a result of this research, a model has been developed to identify the kind of skin cancer (benign or malignant), which will enable dermatologists to move forward with the necessary treatment for their patients.

Deep Convolutional Neural Networks were selected because of the high precision and accuracy values they offer, as well as the very well layered architecture they provide for conducting pixel-by-pixel analysis of image samples.With an accuracy of 98.53%, the model that was used performed a good job of predicting the type of cancer that was present, as can be seen from the findings.the methodology that has been developed has the potential to be useful in linking patients with doctors while reducing the number of unnecessary processes.this study has the potential to encourage governments and business leaders to focus on computer vision as a resource for addressing difficulties in the healthcare industry and to actually plan ahead in the direction of strategies that integrate AI.

In the Future work, using different deep CNN models and improving sample size can improve this study. unique methodology can integrate computer vision with ML algorithms for greater insights.there may be other transfer learning models.increasing training epochs improves accuracy.the proposed methodology's different layers can be piloted.fine-tune hyperparameters with tensor boards.improve the outcome with other optimizers and training algorithm.

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