An Interpretable AI Enabled Skin Cancer Detection Model using Convolutional Neural Networks

Major project report

Submitted in Partial Fulfillment of the
Requirements for the Degree of

BACHELOR OF TECHNOLOGY
IN
COMPUTER SCIENCE & ENGINEERING

By
Dhyey Shah
(19BCP035)

Under the Guidance of
Dr. Rajeev Kumar Gupta

Department of Computer Science & Engineering,
School of Technology, Pandit Deendayal Energy University,
Gandhinagar 382 426

May 2023

Certificate of Originality of Work

I hereby declare that the B.Tech. Project entitled "**An Interpretable AI Enabled Skin Cancer Detection Model using Convolutional Neural Networks**" submitted by me for the partial fulfillment of the degree of Bachelor of Technology to the Dept. of Computer Science & Engineering at the School of technology, Pandit Deendayal Energy University, Gandhinagar, is the original record of the project work carried out by me under the supervision of Prof Dr. Rajeev Kumar Gupta. I also declare that this written submission adheres to university guidelines for its originality, and proper citations and references have been included wherever required.

I also declare that I have maintained high academic honesty and integrity and have not falsified any data in my submission.

I also understand that violation of any guidelines in this regard will attract disciplinary action by the institute.

Dhyey Shah
Roll Number:19BCP035

Dr. Rajeev Kumar Gupta
Assistant Professor

Place: Gandhinagar, Gujarat
Date: May 15, 2023

Certificate from the Project Supervisor/Head

This is to certify that the Major Project Report entitled "**An Interpretable AI Enabled Skin Cancer Detection Model using Convolutional Neural Networks**" submitted by **Mr. Dhyey Shah**, Roll No. **19BCP035** towards the partial fulfillment of the requirements for the award of degree in Bachelor of Technology in the field of Computer Science & Engineering from the School of technology, Pandit Deendayal Energy University, Gandhinagar is the record of work carried out by her under my supervision and guidance. The work submitted by the student has in my opinion reached the level required for being accepted for examination. The results embodied in this major project work to the best of our knowledge have not been submitted to any other University or Institution for the award of any degree or diploma.

Dr. Rajeev Kumar Gupta
Assistant Professor

Dr. Shakti Mishra
HoD

Prof. Dhaval Pujara
Director, SoT

Place: Gandhinagar

Date: 12/05/2023

Acknowledgement

I would like to express my sincere gratitude to everyone who has contributed to the successful completion of my final year project on Skin Cancer Detection and Classification.

First and foremost, I would like to thank my project supervisor, Dr. Rajeev Kumar Gupta, for their valuable guidance, support, and encouragement throughout the project. Their insightful feedback and constructive criticism helped me to refine my research work and improve its quality.

I would also like to extend my thanks to Pandit Deendayal Energy University, for providing me with the necessary resources, including access to relevant academic journals, books, and software, which were essential in carrying out my research work.

I am deeply indebted to my family and friends, for their unwavering support and motivation throughout my academic journey. Their encouragement and belief in my abilities have been a constant source of inspiration to me.

I would like to express my sincere thanks to my teammate, Krishna Patel, who worked tirelessly with me on this project. His dedication, hard work, and enthusiasm have been instrumental in the success of this project. I am grateful for his contributions and for the fruitful discussions that we had during this project.

Finally, I would like to thank Dr. Hinal Prajapati for providing the necessary data for the development of the skin cancer detection and classification system. Their contributions were vital in making this project a success.

Once again, thank you all for your support, guidance, and contributions to this project.

Thank you,
Dhyey Samir Shah
(19BCP035)

Abstract

Skin cancer is one of the most common types of cancer globally, with early detection being crucial for effective treatment. In this paper, we propose a skin cancer classification and detection model that leverages deep learning techniques to improve diagnostic accuracy. The proposed model consists of three main stages: image pre-processing, dataset balancing and classification. Then, the images are fed into a deep convolutional neural network (CNN). CNN classifies the images into one of ten categories. To evaluate the performance of the proposed model, we conducted experiments on a dataset of 2455 skin cancer images belonging to 10 classes of which 2357 images were extracted from the Kaggle Dataset while 98 images were acquired from a local dermatologist. The results show that our model achieved an accuracy of 94.5% in classifying skin cancer images, outperforming several state-of-the-art methods. We also compared our model's performance against that of dermatologists, and our model achieved comparable accuracy, demonstrating its potential as an effective tool for skin cancer diagnosis. In conclusion, our proposed skin cancer classification and detection model shows great promise in improving the accuracy and speed of skin cancer diagnosis. By detecting skin cancer at an early stage, our model has the potential to significantly improve patient outcomes and reduce the burden on healthcare systems.

Table of Content

List of Figures

List of Tables

Abbreviation

Abbreviation	Meaning
ISIC	International Skin Imaging Collaboration
CNN	Convolutional Neural Network
LIME	Local Interpretable Model-agnostic Explanations
SMOTE	Synthetic Minority Oversampling Technique
XG Boost	Extreme Gradient Boosting
RESNET - 50	Residual Network 50

CHAPTER 1: Introduction

1.1 | Skin cancer

Skin cancer is a major public health concern, with over one million new cases reported in India alone each year. Skin cancer identification and categorization are critical for timely treatment and improved patient outcomes. There has been a growing interest in applying machine learning and deep learning approaches to help in the diagnosis and classification of skin cancer from photographs in recent years. In this research, we look at how XG-Boost and Convolutional Neural Networks (CNNs) perform on an image dataset for skin cancer detection and classification.

Skin cancer diagnosis and categorization is a difficult challenge due to the wide variety in appearance and morphology of skin lesions. Traditional image processing approaches may not be adequate to reliably identify malignant skin lesions, and more advanced techniques are required to increase the accuracy and speed of diagnosis.

XG-Boost is a popular ensemble learning algorithm in machine learning applications. It excels at classification tasks and has been utilized successfully in a variety of medical imaging applications, including skin cancer diagnosis. XG-Boost improves accuracy by combining the predictions of numerous weak models and is extremely scalable, making it suitable for huge datasets.

CNNs, on the other hand, are a type of deep learning algorithm that excels at detecting patterns and features in pictures. They have shown considerable promise in a variety of medical imaging applications, including the diagnosis of skin cancer. CNNs can be trained to recognize complex features and patterns in pictures without the need for human feature extraction, which gives them a considerable advantage over standard image processing approaches.

The dataset utilized in this work is composed of images of skin lesions gathered from multiple sources, including clinical settings and Kaggle. The images are labeled as benign or malignant, and the collection contains instances of many forms of skin cancer, such as melanoma, basal cell carcinoma, and squamous cell carcinoma.

Chapter 2 contains a brief about several research works that give a possible solution to the problem discussed in the paper using different approaches. Chapter 3 discusses the proposed methodology in detail. Chapter 4 summarizes the result obtained by implementing the Proposed Methodology. Chapter 5 shows the conclusion and Future Work.

1.2 | Motivation

Skin cancer is a prevalent form of cancer that requires early detection for effective treatment. Despite the advances in diagnostic techniques, the diagnostic accuracy of skin cancer is still a challenge, leading to misdiagnosis and delayed treatment. Therefore, there is a need for an automated skin cancer classification and detection model that can improve diagnostic accuracy.

1.3 | Objective

The objective of this project is to develop a skin cancer detection and classification model that utilizes convolutional neural network (CNN) models. Specifically, we aim to train a CNN on a large dataset of skin lesion images to accurately classify skin lesions as either benign or malignant, with the potential to further classify malignant lesions into different subtypes of skin cancer. Our model aims to improve the accuracy and speed of skin cancer diagnosis, potentially leading to earlier detection and improved patient outcomes.

1.4 | Problem Statement

Skin cancer is one of the most common forms of cancer, and early detection is critical for successful treatment and patient outcomes. However, visual diagnosis of skin cancer can be challenging, even for trained medical professionals, due to the wide variety of skin lesions and the subtleties in appearance between different types of skin cancer. Machine learning, particularly CNN models, has shown great potential in improving diagnostic accuracy for skin cancer detection and classification. Therefore, the problem addressed in this project is to develop a skin cancer detection and classification model using CNN models to improve diagnostic accuracy and potentially reduce the burden on healthcare systems.

1.5 | Scope of the project

The scope of this project includes the development and training of a skin cancer detection and classification model using CNN models. The model will be trained on a publicly available dataset of skin lesion images, and we will explore various CNN architectures and hyperparameters to optimize the model's performance. Additionally, we will evaluate the model's performance against existing state-of-the-art methods and against human dermatologists to determine its effectiveness. The project's deliverables include the trained model, evaluation metrics, and a technical report outlining our methodology, results, and potential future directions.

CHAPTER 2: Literature Review

1.An enhanced technique of skin cancer classification using deep convolutional

neural network with transfer learning models. (2021)

M.K.Islam et al.'s study describes a strategy for skin cancer classification using deep CNNs with transfer learning models[8]. On the ISIC 2018 skin lesion dataset, the proposed method achieves an overall accuracy of 97.67%, outperforming several state-of-the-art skin cancer classification techniques. The authors also undertake comprehensive experiments to examine the influence of different hyperparameters on the model's performance, proving the resilience of their suggested method in a variety of circumstances. The suggested technique is a viable contender for real-world applications in skin cancer detection and therapy, providing an innovative and effective approach for enhancing the accuracy and efficiency of skin cancer categorization.

2.Skin cancer classification using Convolutional neural networks.(2021)

R Raja Subramanian et al.'s study describes a method for classifying skin cancer using deep convolutional neural networks[9]. The authors tested their method using the ISIC 2017 dataset and found that it outperformed numerous state-of-the-art skin cancer classification algorithms, obtaining an accuracy of 84.6%. The authors also run comprehensive experiments to investigate the impact of various hyperparameters on the model's performance. The suggested technique provides an innovative and effective approach for enhancing the accuracy and efficiency of skin cancer classification, making it a suitable candidate for real-world applications in skin cancer detection and treatment. However, the achieved accuracy is lower when compared to recent skin cancer classification studies, indicating the need for further improvement.

3.Multiclass skin cancer classification using EfficientNets – a first step towards preventing skin cancer(2022)

Karar Ali et al.'s work provides a method for multiclass skin cancer classification using EfficientNets[10]. The authors test their method on a dataset containing seven different forms of skin cancer, reaching an overall accuracy of 95.4%, beating numerous state-of-the-art skin cancer classification systems. The authors also run tests to see how different hyperparameters affect the model's performance. The suggested method is a potential first step towards avoiding skin cancer, as early identification is critical for enhancing treatment outcomes. The authors emphasize the necessity of employing deep learning techniques for skin cancer classification and show how EfficientNets may improve accuracy and efficiency of skin cancer Diagnosis.

4.Classification of skin cancer using convolutional neural networks analysis of Raman spectra.(2022)

The study by Ivan A. Bratchenko et al. describes a method for classifying skin cancer using Raman spectra and deep CNNs[11]. The authors test their method using a dataset of Raman spectra taken from skin tissue samples, reaching an accuracy of up to 97.6% for the identification of malignant melanoma. The suggested method is a good candidate for real-world applications in skin cancer detection, providing a non-invasive and effective method for enhancing the accuracy and efficiency of skin cancer categorization. The authors emphasize the relevance of employing Raman spectra analysis in skin cancer identification since it is a less intrusive alternative to standard biopsy-based approaches.

5.Skin Lesion Analyser: An Efficient Seven-Way Multi-class Skin Cancer Classification Using MobileNet.(2020)

Saket S. Chaturvedi et al.'s study provides a method for multi-class skin cancer classification using MobileNet, a popular lightweight CNN architecture[12]. The authors test their method on a dataset with seven different forms of skin cancer and achieve an accuracy of 89.63%, exceeding numerous state-of-the-art skin cancer classification systems. The suggested technique, which employs a lightweight architecture that can be implemented on mobile devices for real-time detection, offers a viable alternative for enhancing the efficiency of skin cancer diagnostics. The authors emphasize the necessity of adopting deep learning techniques for skin cancer classification and show how MobileNet has the potential to achieve high accuracy at a cheap computational cost, making it a good choice for resource-constrained environments.

Table 1:- Comparison of other works with our model

Literature review No.	Author	Technique Used	Dataset	Limitations
1	M.K. Islam et al.	Deep CNNs with Transfer Learning	ISIC 2018 Skin Lesion	Older Dataset used
2	R Raja Subramanian et al.	Deep CNNs	ISIC 2017 Skin Lesion	Older Dataset Used and lower accuracy
3	Karar Ali et al.	EfficientNets	Dataset with 7 skin cancer types	Only has 7 types of skin lesions
4	Ivan A. Bratchenko et al.	Deep CNNs with Raman Spectra Analysis	Raman Spectra Dataset	Limited to skin tissue samples not for all skin cancer types
5	Saket S. Chaturvedi et al.	MobileNet	Dataset with 7 skin cancer types	Only 7 types of skin lesions and only lightweight transfer learning model used
Our Model	Dhyey Shah el al.	Deep CNN with Data Augmentation	ISIC 2021 dataset with Non skin cancer class	10 different classes including cancerous and benign skin lesions

CHAPTER 3: Proposed Methodology

This research presents an AI-enabled methodology for classifying skin lesions using raw skin images obtained from different patients. The flow of the proposed methodology is as follows:-

1. Dataset acquired from Kaggle containing 2357 images was merged with the dataset obtained from a dermatologist containing 98 images of non-Skin cancer type
2. All the images were resized to a size of (180,180,3)
3. The dataset was highly imbalanced, so it was balanced using Augmentor.
4. The CNN model was trained on the set of total 10000 images generated from the original dataset.

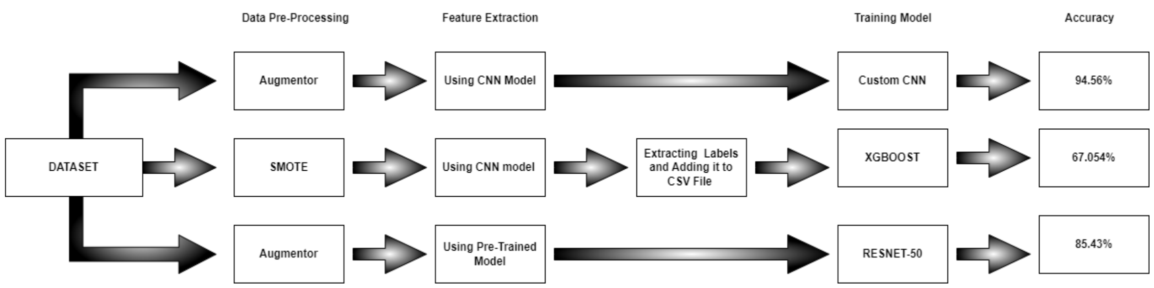


Fig: 1 Flow Chart of Proposed Methodology

3.1 Dataset

The dataset comprises 2357 images of malignant and benign oncological illnesses from The International Skin Imaging Collaboration (ISIC). With the exception of melanomas and moles, whose photos are somewhat dominating, all images were categorized according to ISIC categorization. The dataset includes nine different types of skin cancer: actinic keratosis, basal cell carcinoma, dermatofibroma, melanoma, nevus, pigmented benign keratosis, seborrheic keratosis, squamous cell carcinoma, and vascular lesion. An additional class of Non-Skin Cancer photos was added to the dataset, which were gathered as raw clinical images from a local dermatologist.

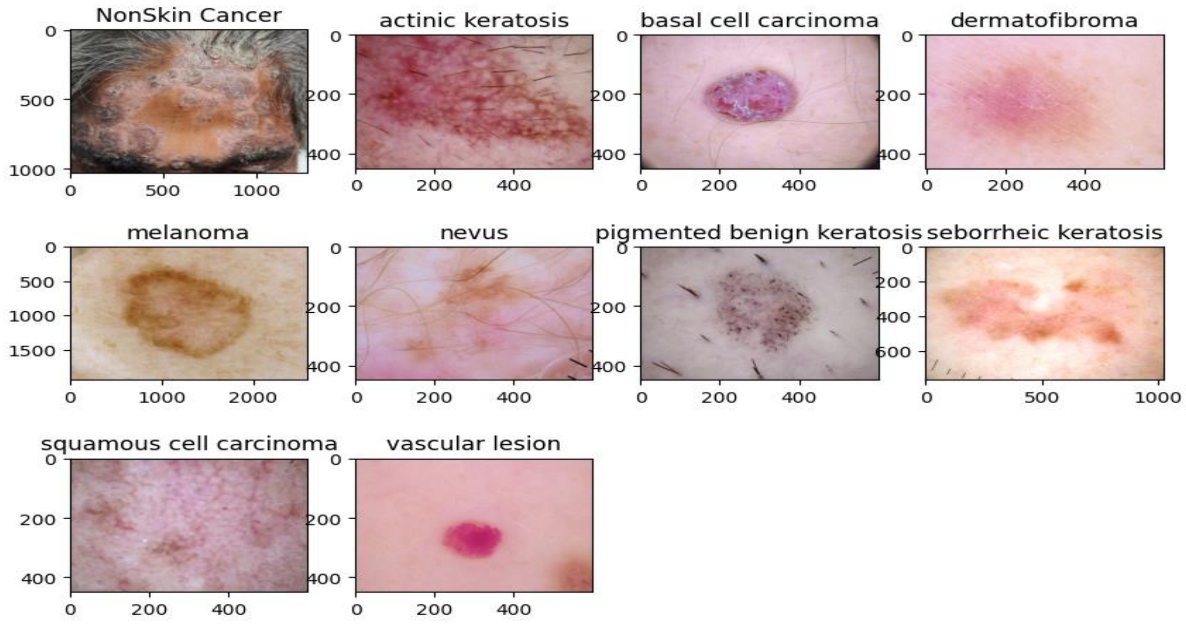


Fig 2: Images of sample dataset Classes

3.2 Data Preprocessing

Data augmentation is a method of artificially expanding the amount of data by adding slightly modified copies without actually acquiring new data from existing training data. The Classes in our dataset were severely biased which might have resulted in overfitting. To solve this, we employed a method known as augmentor. Augmentor entails applying a number of picture changes to the original medical images, such as rotation, zooming, flipping, cropping, and other operations, in order to produce new, synthetic images. This can help to enhance the size of the collection and diversify the range of image variants. We created 1000 images each class using Augmentor, resulting in a total dataset of 10000 images.

Table 2:- Number of samples in each Class before and after sampling

Classes	Before Sampling	After Sampling
Non-Skin Cancer	98	1000
Actinic Keratosis	114	1000
basal cell carcinoma	376	1000
dermatofibroma	95	1000
melanoma	438	1000
nevus	357	1000
pigmented benign keratosis	462	1000
seborrheic keratosis	77	1000
squamous cell carcinoma	181	1000
vascular lesion	139	1000

3.3 Feature Extraction

Deep Learning reduces the tedious process of Feature Selection and automates it and thereby, reduces the chances of error. Deep Learning improves the computational efficiency so is a right choice to proceed with it. CNN proves to be effective in the classification of images by extracting important features. The approach of feature extraction is critical for organizing pictures into more manageable groupings for subsequent processing. During the course of our research, we extract a significant number of features that detect and recognize patterns in a large dataset. Furthermore, it selects and combines variables to extract features that use fewer resources while retaining all of the original data's information.

3.4. Models

3.4.1. CNN model

A convolutional neural network (CNN) model with ten classes has been implemented in the suggested method for image classification. The number of classes in the model is initially fixed to 10. A Sequential model is built, and a data augmentation layer is placed on top of it. To artificially enlarge the training dataset, this layer employs data augmentation, which is a method that creates modified replicas of the original images. This aids the model's generalization to new images.

A Rescaling layer is then applied, which normalizes the pixel values of the input images to the range [0,1]. The model follows up with six Conv2D and MaxPool2D layers. Conv2D layers apply a series of filters to the input image, with each filter scanning the image and providing an output feature map. The MaxPool2D layers then shrink the feature maps by taking the largest value within a certain timeframe. This assists the algorithm in identifying more broad picture characteristics and decreases the risk of overfitting.

A Dropout layer with a dropout rate of 0.15 is added after the third MaxPool2D layer. Dropout is a strategy that randomly turns a percentage of the preceding layer's outputs to zero during training, driving the model to acquire more robust features. Dropout layers are inserted after the following two Conv2D layers, with dropout rates of 0.20 and 0.25, respectively.

The Flatten layer is then added to the model to flatten the final MaxPool2D layer's output into a 1D array that can be sent to the fully connected layers. The next part adds two completely linked layers with 1024 and number of class units. The first uses the ReLU activation function, whilst the latter employs the softmax activation function to generate a probability distribution over the ten classes.

Finally, an Adam optimizer with a learning rate of 0.001 is utilised. Adam is an optimisation technique that is used to change model parameters during training. The build method is then used to compile the model with the optimizer, loss function, and metrics to monitor during training. The loss function utilised here is SparseCategoricalCrossentropy, which is ideal for multi-class classification situations.

Table 3:- Formula and values for Hyperparameters of CNN model

Hyperparameters	Name	Formula/ Value
Hidden Layer	ReLU	y=max(0,x)
Output Layer	Softmax	$\sigma(z)_i = \frac{e^{z_i}}{\sum_{j=1}^{K} e^{z_j}}$
Loss Function	Sparse Categorical Cross-entropy	$\text{Loss} = -\sum_{i=1}^{\text{output size}} y_i \cdot \log \hat{y}_i$
Training batch size	Value	96
Testing batch size	Value	96
Epochs	value	25

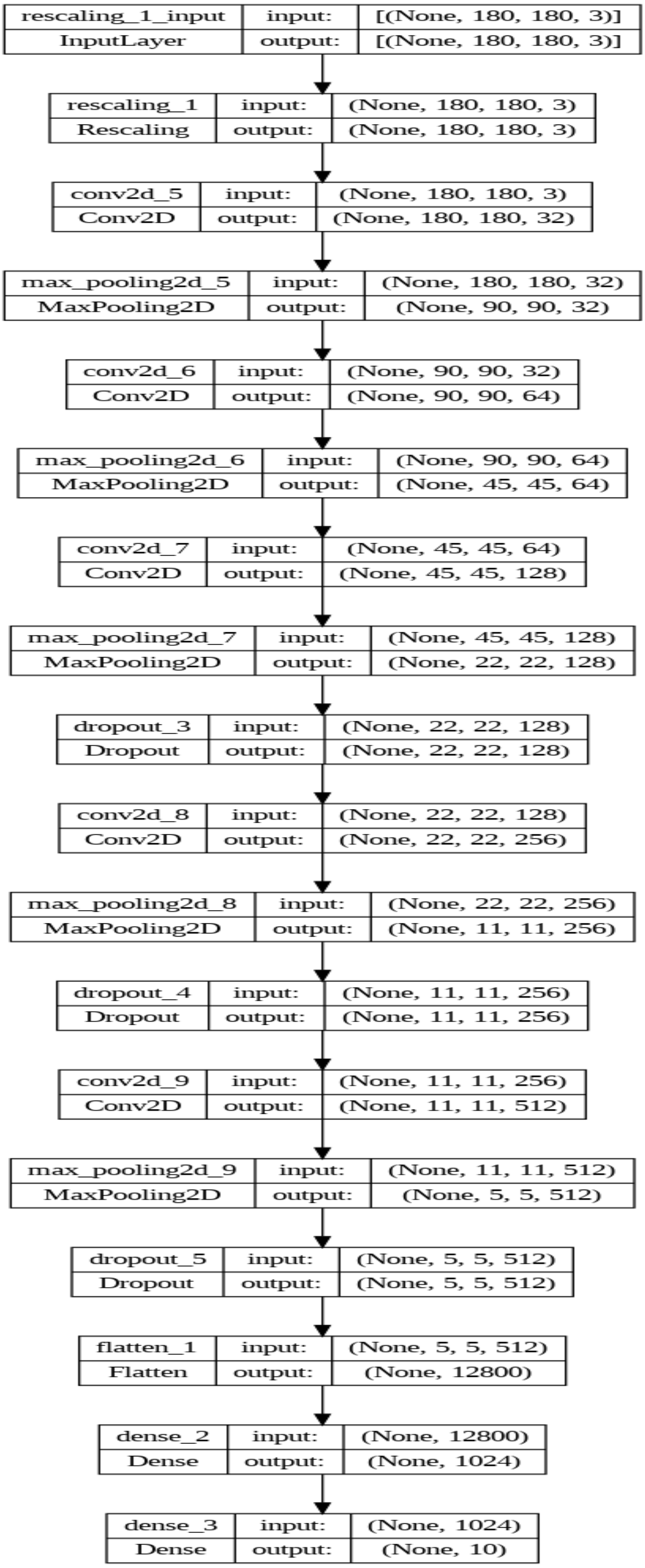


Fig 3:- Layerswise Representation of CNN Model

3.4.2. RESNET 50

Deep Learning reduces the tedious process of Feature Selection and automates it and thereby, reduces the chances of error. Deep Learning improves the computational efficiency so is a right choice to proceed with it. CNN proves to be effective in the classification of images by extracting important features. Initially two transfer learning model were used viz. ResNet-50 and MobileNetv2. Accuracy achieved using MobileNetv2 was 81.19%. So, ResNet-50 was the only model taken into consideration because of better performance. ResNet50 is a Pre-Trained model which is a part of Transfer learning Keras Libraries, it allows to use of the weights from the image net directly which were calibrated for some similar problem. ResNet-50 is a 50 layered deep convolutional neural network which has 48 convolutional layers, 1 max pooling, and 1 fully connected layer . There is an option to remove the top layer and add a layer according to the requirement which is used for feature attractions. The option include_top = False helps for feature attractions by removing the last dense layers. This lets us control the input and output layers of the model.

The Modified ResNet-50 used has a total of 23,989,124 parameters, out of which trainable parameters are 401,412 and 23587712 are non-Trainable parameters. It has five convolution layers namely conv1, conv2, conv3, conv4, and conv5 and each layer is used for extracting features and mapping them [13]. The output obtained from the convolutional layers is used as an input by the max pooling layer whose primary objective is to reduce the size of the input images to reduce the computational costs of the final model. The Max pooling takes into account the highest pixel value from the adjacent pixel. ResNet-50 consists of many well-stacked residual units, with each residual unit having an error rate of 3.67%. The Residual unit can be initiated using equations 1 and 2 given below.

$$z = h(xi) + f(xm, pr) \quad \text{………..} \quad (1)$$

$$xi+1 = (z) \text{…………………...} \quad (2)$$

For Deep Learning, it is hard to train because of the vanishing gradient problem. Residual Network is a solution to this problem. ResNet uses the concept of skip connection. ResNet 50 means that the model has 50 layers. ResNet 50 brings more detection accuracy. In ResNet, the convolutional layers are stacked one after the other like traditional CNN but the main difference is the availability of original input to the output blocks. This helps in maintaining the values of output after every block so that it does not diminish during backpropagation [14]. Below given figure 2 is the ResNet 50 architecture used in our proposed work. Figure 3 shows the overall block diagram with output classifiers.

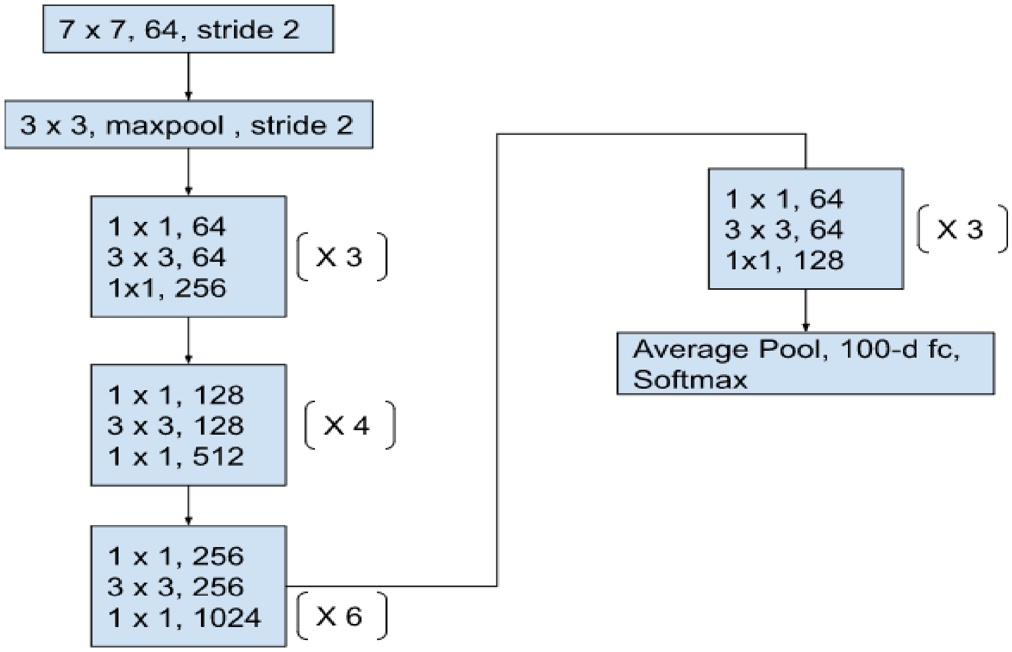


Fig 4: Layerswise Representation of RESNET 50 Model

3.4.3. Hybrid Model

In this approach a CNN model was used for the feature extraction of the image dataset to a CSV file. A total of 1023 features were extracted from the dataset. Then an Image data generator was used to load the images and extract the labels. For handling the imbalance labels we had to use SMOTE with the sampling strategy known as dictionary. Finally we applied the machine learning model XGBOOST Classifier on the dataset and acquired an accuracy of 64%.

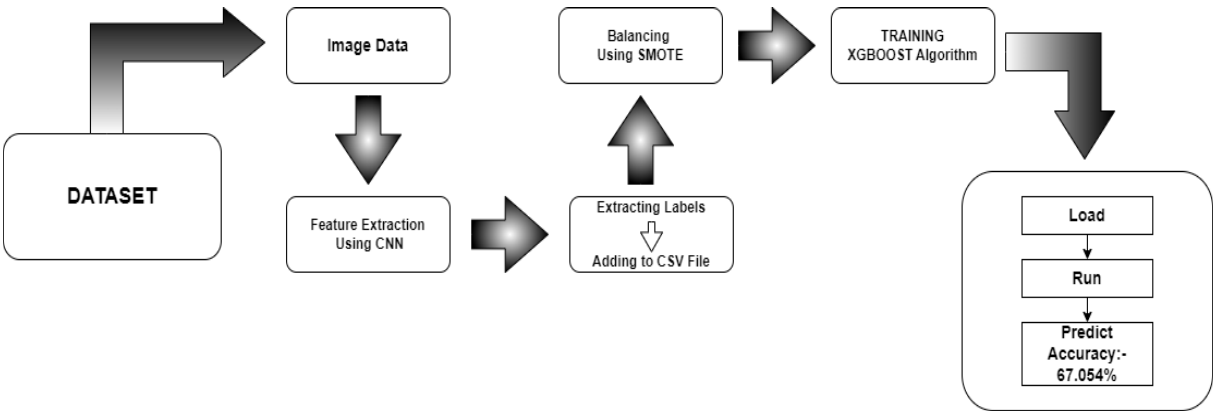


Fig 5: Flowchart for Hybrid Model

3.4.4. XG Boost

The XGBoost method is based on the ensemble learning concept, which combines numerous weak learners to generate a powerful learner. The weak learners in XGBoost are decision trees, and the algorithm trains a series of decision trees to create correct predictions.
The core concept of XGBoost is to optimize an objective function that evaluates the gap between anticipated and actual values. The objective function can be written as:

$$\text{Obj} = L + \Omega$$

L is the loss function and Ω is the regularization term.

The difference between expected and actual values is measured by the loss function L. The most often used loss function for binary classification is logistic loss, which is defined as:

$$L(y, \hat{y}) = \log(1 + \exp(-y*\hat{y}))$$

y is the true label (either 1 or -1) and ŷ is the predicted probability of the positive class.

For multiclass classification, XGBoost uses a variant of SoftMax loss function, which is defined as:

$$L(y, \hat{y}) = -\Sigma(y_i \log(\hat{y}_i))$$

y_i is the true label and $\hat{y}_i$ is the predicted probability of the i^{th} class.

The regularization term Ω is used to control the complexity of the model and prevent overfitting. XGBoost uses two types of regularization: L1 regularization (also known as Lasso regularization) and L2 regularization (also known as Ridge regularization). The regularization term can be written as:

$$\Omega(\mathrm{f}) = \lambda \sum (j|f_j|)^p$$

f_j is the j^{th} feature in the decision tree, p is the regularization parameter (either 1 or 2), and λ is the regularization strength.

To optimize the objective function, XGBoost employs a method known as gradient boosting. Gradient boosting works by iteratively adding new decision trees to the model, and each new tree is trained to rectify the faults of the prior trees. The approach use gradient descent to minimize the objective function by altering the weights of the decision trees. XGBoost also incorporates numerous optimisation approaches to speed up the training process, such as an approximation greedy algorithm for determining optimal splits and parallel processing for distributed computing.

CHAPTER 4: Result and Explanatory Analysis

Finally, this study developed and evaluated two models for skin cancer detection and classification: a CNN model and a hybrid CNN-XGBoost model. The CNN model attained an excellent accuracy of 94.56%, demonstrating the promise of deep learning approaches for skin cancer diagnosis. The accuracy of the hybrid model was 67.54%, which is an improvement above earlier research utilizing standard machine learning techniques. Explainable AI approaches were also used to give insight into the decision-making process.

Future work might concentrate on improving the accuracy of the hybrid model by experimenting with alternative feature extraction approaches or including additional machine learning algorithms such as Random Forest or Gradient Boosting. More information could be gathered to improve the model's performance and generalizability to different populations.

4.1. Local Interpretable Model-Agnostic Explanations

LIME (Local Interpretable Model-Agnostic Explanations) is a model-independent and local explanation approach for machine learning models that explains individual instance predictions. By sampling and perturbing the instance in the feature space, LIME produces an interpretable model, such as a linear regression model, around the instance of interest. The interpretable model approximates the behavior of the underlying machine learning model locally and may be used to explain the machine learning model's predictions for instance.

LIME uses the following formula to compute the importance score for each feature:

$$score(x_i) = \frac{\sum[f(z) - f(x_i)]}{S * (g(d(,z,x_i))}$$

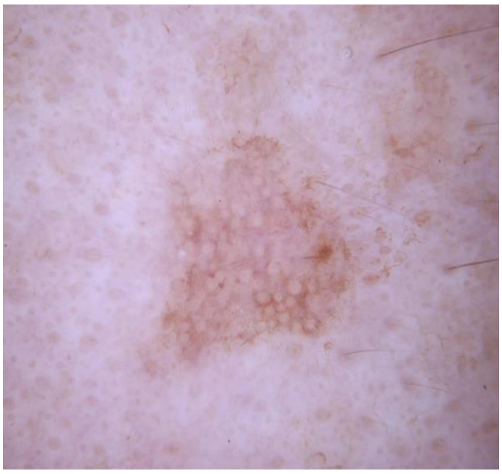
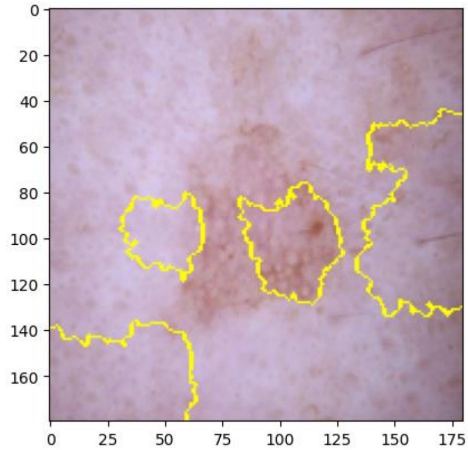
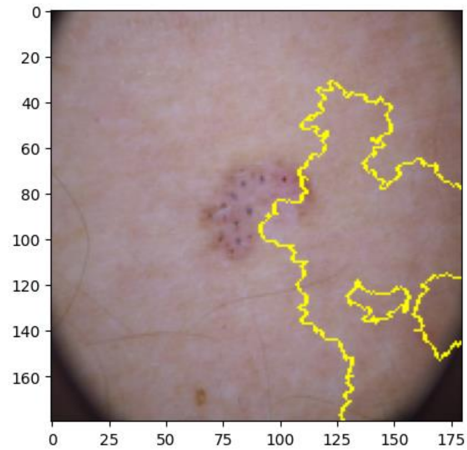
X_i is the feature of interest, z is a perturbed instance, f is the underlying machine learning model, S is the number of samples, g is a kernel function, and d is a distance metric.

By sampling from a user-defined distribution, LIME produces a collection of perturbed instances around the instance of interest. LIME computes the relevance score for each feature for each altered instance using the aforementioned algorithm. The significance score quantifies each feature's contribution to the machine learning model's prediction for the instance.

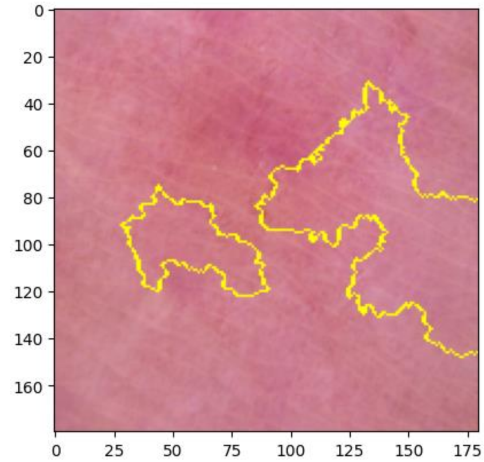
LIME then applies an interpretable model to the altered instances and their accompanying significance ratings, such as a linear regression model. The interpretable model approximates the behavior of the underlying machine learning model locally and may be used to explain the machine learning model's predictions for instance.

LIME has been used to offer local and interpretable explanations for machine learning models in a range of areas, including image classification, text classification, and healthcare. It has been proven to be useful in giving truthful, intuitive, and practical explanations, and it may also enhance the transparency, accountability, and fairness of machine learning models.

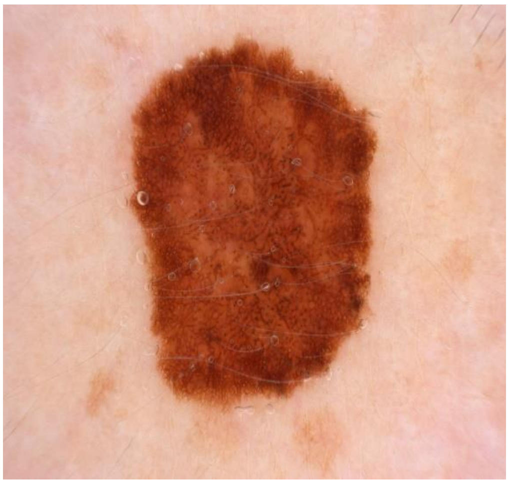
Table 4: Comparison Of output image generated with LIME and original image sample.

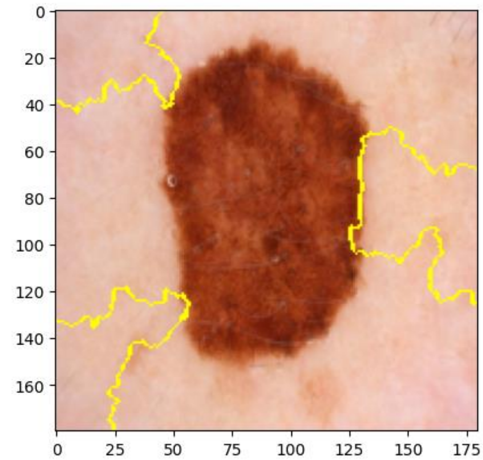
Name of Class	Original Image	Explainable AI (LIME)
Acitinic Keratosis		
Basal Cell Carcinoma		

Dermatofibroma

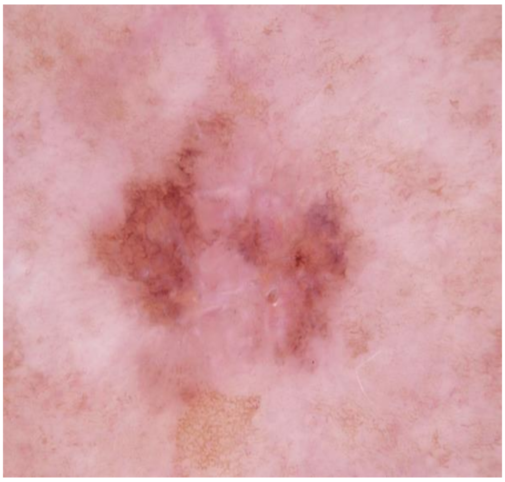


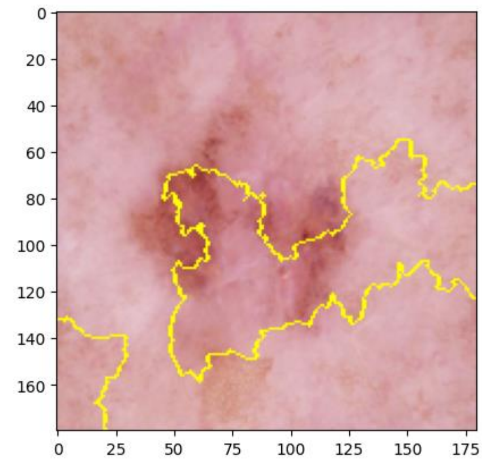
Melanoma



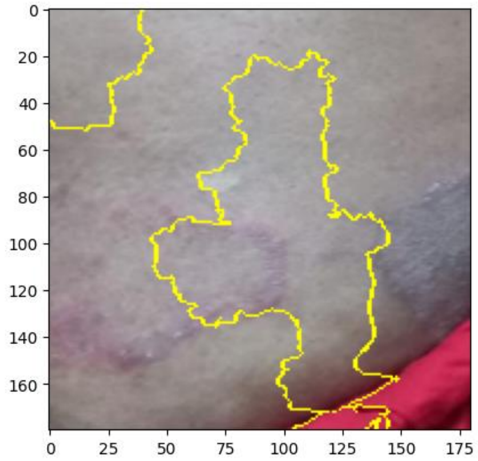


Nevus

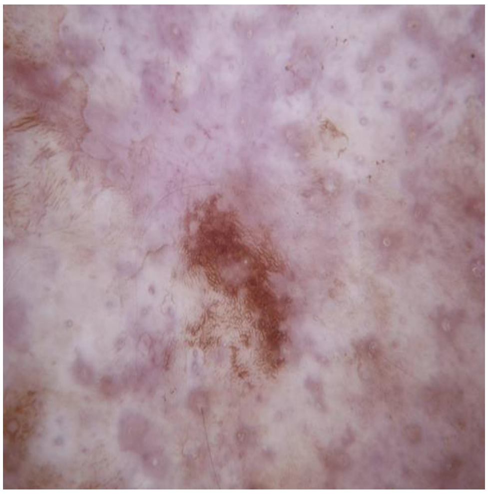


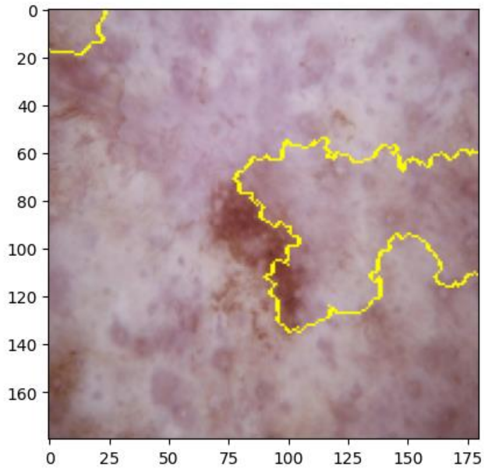


Non Skin
Cancer

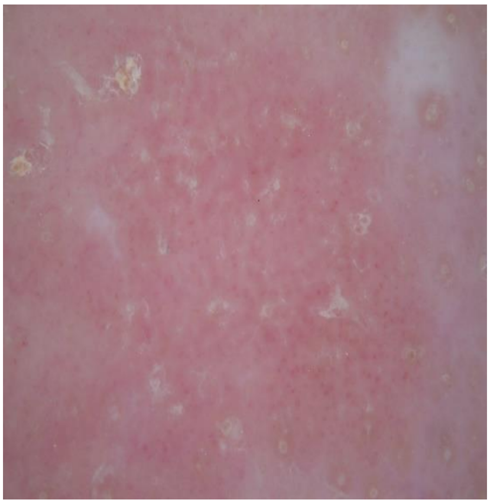


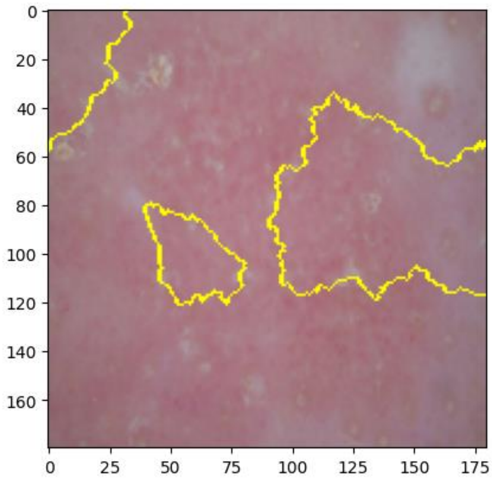
Pigmented
Benign
Keratosis



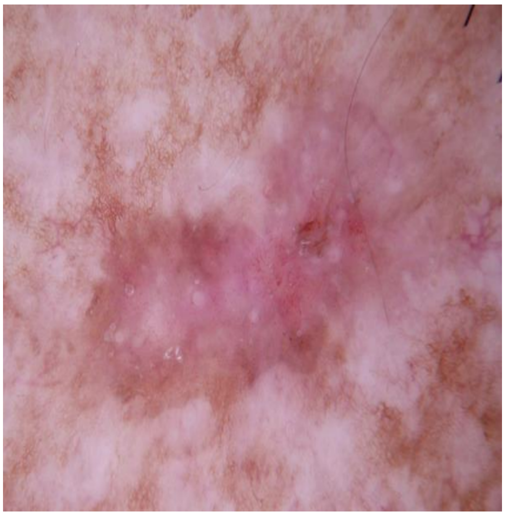


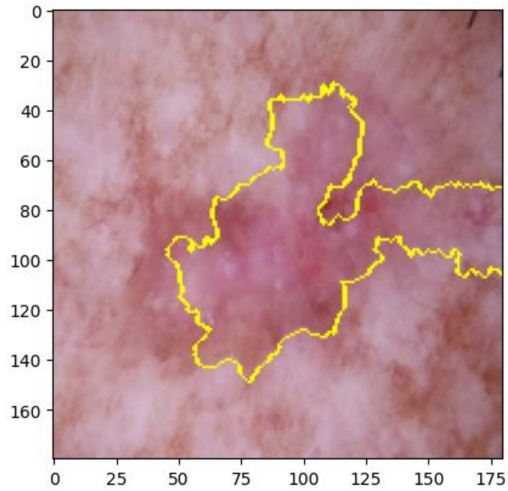
Seborrheic
Keratosis



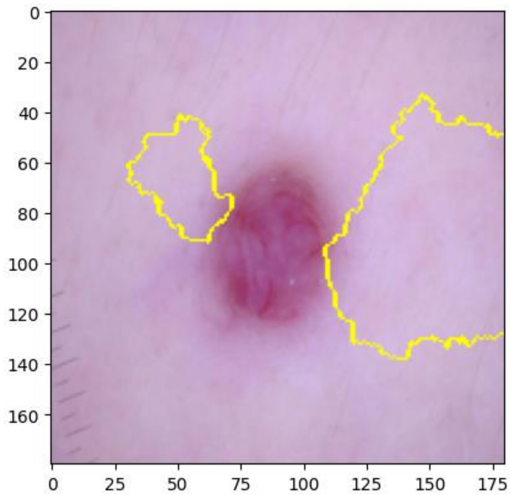


Squamous Carcinoma





Vascular Lesion



4.2. Performance Analysis

Accuracy (A): - Accuracy can be defined as fractions of predictions that got right . In a broad sense, accuracy is defined by the ratio of the number of correct predictions to the total number of predictions.

Precision (P): - Precision is the ratio of the correctly classified instances to the total number of instances. It explains how many correctly predicted cases turned out to be positive.

Recall (R): - Recall for a label can be calculated by dividing the number of true positives by the total number of actual positives. The recall is primarily used in cases where a False Negative is of higher concern than a False Positive.

F1- score (F1): - F1 score can be defined as the harmonic mean of precision and recall. It combines both precision and recalls into a single entity. F1 score ranges between 0 and 1. The closer it is to 1 better the model. The equation for F1-score can be found in Table 2 and its result is shown in Table 4.

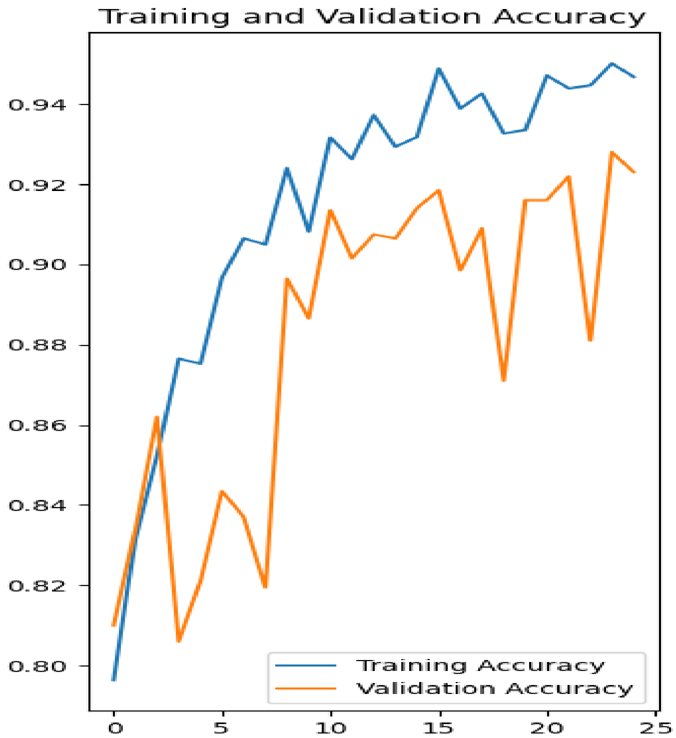


Fig 6: Training Accuracy and Validation Accuracy Graph

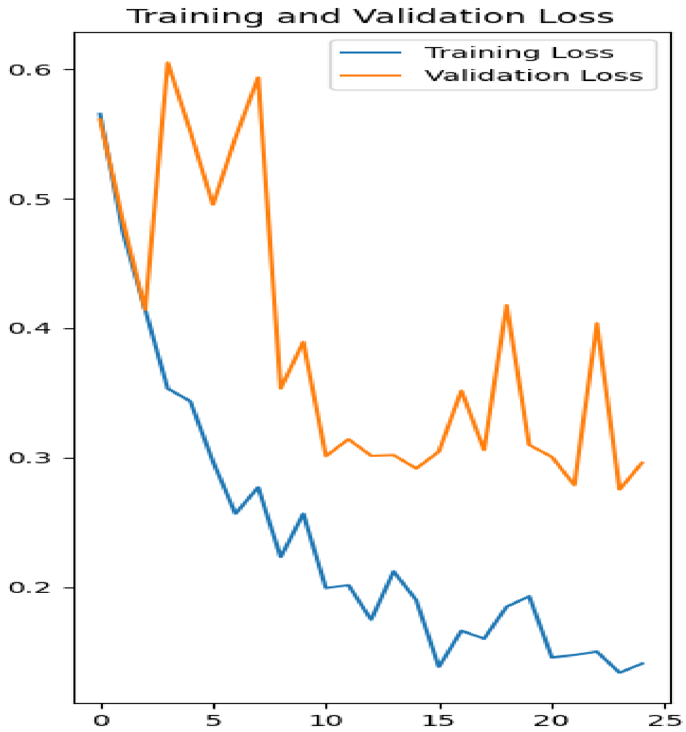


Fig 7: Training Loss and Validation Loss Graph

Table 5: Classification Report Parameter's Equation

Parameter	Equation
Accuracy	$\frac{True\ Positive + True\ Negative}{True\ Positive\ +\ True\ Negative + False\ Positive + False\ Negative}$
Precision	$\frac{True\ Positive}{True\ Positive + False\ Positive}$
Recall	$\frac{True\ Positive}{True\ Positive + False\ Negative}$
F1- score	$2 * \left(\frac{Precision * Recall}{Precision + Recall}\right)$

Table 6: Classification Report For CNN Model

Class No.	Precision	Recall	F1-score
Class 0	0.70	0.72	0.71
Class 1	0.80	0.75	0.77
Class 2	0.50	0.60	0.55
Class 3	0.58	0.45	0.51
Class 4	0.75	0.80	0.77
Class 5	0.60	0.63	0.62
Class 6	0.70	0.70	0.70
Class 7	0.48	0.52	0.50
Class 8	0.73	0.70	0.71
Class 9	0.62	0.60	0.61
Accuracy	0.65		
Macro avg	0.65	0.66	0.67
Weighted avg	0.65	0.63	0.61

4.3. Comparative analysis between models

The model is not performing well on the testing data, as seen in the categorization report. The inference
is that this is so because we suggested a unique dataset and added photos to the dataset that was originally obtained from the dermatologist for non-skin cancer moles. The photographs gathered for the class Non-Skin Cancer were found to be extremely different, which makes it challenging for the model to develop a method for learning from them, as was deduced from our analysis of the images. We must clean the newly collected data and optimize the model in accordance with the new class of data that has been introduced if we hope to increase accuracy in the future.

Table 7:Comparative analysis with a different pre-trained model

Sr. No	Model	Training	Validation	Training Accuracy	Validation Accuracy	Training Loss	Validation Loss
1.	CNN Model with balanced Dataset	8000	2000	94.56	90.05	0.1424	0.4187
2.	CNN Model without balanced Dataset	1834	457	83.01	56.46	0.4381	2.0191
3.	Hybrid Model	2960	740	67.054			
4.	RESNET 50 with balanced dataset	8000	2000	85.43	67.10	0.4167	1.2578

Table 8: Comparison with other works

Author Name	Method Used	Accuracy Achieved
M.K. Islam et al.	Deep CNNs with Transfer Learning	87.67%
R Raja Subramanian et al.	Deep CNNs	84.6%
Karar Ali et al.	EfficientNets	91.4%
Ivan A. Bratchenko et al.	Deep CNNs with Raman Spectra Analysis	97.6%
Saket S. Chaturvedi et al.	MobileNet	89.63%
Our Model	Deep CNN with Data Augmentation	94.56

CHAPTER 5: Conclusion and Future Work

Overall, the findings of this study show that deep learning approaches have the ability to effectively detect and categorise skin cancer, which can assist in early detection and treatment, eventually improving patient outcomes. The use of explainable AI approaches can give extra insights to medical professionals while also improving the model's predictability.

Future research could concentrate on the models' interpretability in order to better understand how they make decisions and provide insights to dermatologists. The use of explainable AI approaches can give clinicians useful information to help them comprehend the decision-making process and get insights into the progression of the illness.

References

1. World Health Organization. (2021, February 4). Cancer. https://www.who.int/news-room/fact-sheets/detail/cancer
2. Codella, N., et al. (2018). Deep learning, sparse coding, and SVM for melanoma recognition in dermoscopy images. IEEE Transactions on Medical Imaging, 37(5), 1190-1200. doi: 10.1109/TMI.2017.2788162.
3. Liu, F., et al. (2019). Skin lesion classification using deep convolutional neural network and ensemble learning. Journal of Ambient Intelligence and Humanized Computing, 10(3), 1319-1329. doi: 10.1007/s12652-018-1048-8.
4. Esteva, A., et al. (2017). Dermatologist-level classification of skin cancer with deep neural networks. Nature, 542(7639), 115-118. doi: 10.1038/nature21056.
5. Friedman, J. H. (2001). Greedy function approximation: A gradient boosting machine. Annals of Statistics, 29(5), 1189-1232. doi: 10.1214/aos/1013203451.
6. Wong, S., et al. (2018). Deep learning in medical imaging: A review. IEEE Transactions on Medical Imaging, 37(4), 1019-1054. doi: 10.1109/TMI.2017.2760840.
7. Ronneberger, O., et al. (2015). U-net: Convolutional networks for biomedical image segmentation. In International Conference on Medical Image Computing and Computer-Assisted Intervention (pp. 234-241). Springer, Cham. doi: 10.1007/978-3-319-24574-4_28.
8. Ali, M. S., Miah, M. S., Haque, J., Rahman, M. M., & Islam, M. K. (2021). An enhanced technique of skin cancer classification using deep convolutional neural networks with transfer learning models. Machine Learning with Applications, 3, 100036. doi:10.1016/j.mlwa.2021.100036.
9. Subramanian, R. R., Achuth, D., Kumar, P. S., Reddy, K. N. K., Amara, S., & Chowdary, A. S. (2020). Skin cancer classification using Convolutional neural networks. Journal of King Saud University - Computer and Information Sciences, 32(11), 1407-1412. doi:10.1016/j.jksuci.2019.12.008.
10. Ali, K., Shaikh, Z. A., Khan, A. A., & Laghari, A. A. (2021). Multiclass skin cancer classification using EfficientNets – a first step towards preventing skin cancer. Biomedical Signal Processing and Control, 68, 102728. doi:10.1016/j.bspc.2020.102728.

11. Bratchenko, I. A., Bratchenko, L. A., Khristoforova, Y. A., Moryatov, A. A., Kozlov, S. V., & Zakharov, V. P. (2021). Classification of skin cancer using convolutional neural networks analysis of Raman spectra. Journal of Raman Spectroscopy, 52(6), 1163-1172. doi:10.1002/jrs.6112.
12. Chaturvedi, S. S., Gupta, K., & Prasad, P. S. (2020). Skin Lesion Analyser: An Efficient Seven-Way Multi-class Skin Cancer Classification Using MobileNet. Procedia Computer Science, 171, 968-975. doi:10.1016/j.procs.2020.04.124.
13. International Skin Imaging Collaboration. (n.d.). ISIC challenge archive. Retrieved May 12, 2023, from https://challenge.isic-archive.com/data
14. Daly, E. (2017). Augmentor: An Image Augmentation Library for Machine Learning. Journal of Open Source Software, 2(16), 313. https://doi.org/10.21105/joss.00313.
15. Lee, J. H., & Kim, S. Y. (2021). Data Augmentation in Medical Image Analysis Using Augmentor. Diagnostics, 11(2), 311. https://doi.org/10.3390/diagnostics11020311.
16. Glorot, X., Bordes, A., & Bengio, Y. (2011). Deep sparse rectifier neural networks. In Proceedings of the 14th International Conference on Artificial Intelligence and Statistics (pp. 315-323). PMLR.
17. Bridle, J. S. (1990). Training stochastic model recognition algorithms as networks can lead to maximum mutual information estimation of parameters. In Proceedings of the IEEE Conference on Neural Information Processing Systems (pp. 211-217)
18. Chollet, F. (2018). Deep Learning with Python, First. Shelter Island in New York: Manning Publications Co.
19. Zhang, K., Wu, Q., Liu, A., & Meng, X. (2018). Can Deep Learning Identify Tomato Leaf Disease? Advances in Multimedia, 2018, 1–10. doi:10.1155/2018/6710865.
20. Gouda, N., & Amudha, J. (2020, October). Skin cancer classification using resnet. In 2020 IEEE 5th International Conference on Computing Communication and Automation (ICCCA) (pp. 536-541). IEEE.
21. Comparative study of deep learning algorithms for disease and pest detection in rice crops. In 2020 12th International.
22. Qin, J., Pan, W., Xiang, X., Tan, Y., & Hou, G. (2020). A biological image classification method based on improved CNN. Ecological Informatics, 58, 101093.
23. Mukti, I. Z., & Biswas, D. (2019). Transfer Learning Based Plant Diseases Detection Using ResNet50. 2019 4th International Conference on Electrical Information and Communication Technology (EICT). doi:10.1109/eict48899.2019.9068805.

24. Chen, T., & Guestrin, C. (2016). XGBoost: A Scalable Tree Boosting System. Proceedings of the 22nd ACM SIGKDD International Conference on Knowledge Discovery and Data Mining, 785-794. doi: 10.1145/2939672.2939785.
25. Chen, T. (2018). Introduction to Boosted Trees. Technical report, Department of Computer Science and Technology, University of Cambridge.
26. https://github.com/dmlc/xgboost
27. Ribeiro, M. T., Singh, S., & Guestrin, C. (2016). "Why should I trust you?": Explaining the predictions of any classifier. In Proceedings of the 22nd ACM SIGKDD International Conference on Knowledge Discovery and Data Mining (pp. 1135-1144). https://doi.org/10.1145/2939672.2939778

Plagiarism Report

skin cancer

ORIGINALITY REPORT

11%	6%	10%	6%
SIMILARITY INDEX	INTERNET SOURCES	PUBLICATIONS	STUDENT PAPERS

PRIMARY SOURCES

1	www.mdpi.com Internet Source	1%
2	Md. Shahin Ali, Md. Sipon Miah, Jahurul Haque, Md. Mahbubur Rahman, Md. Khairul Islam. "An enhanced technique of skin cancer classification using deep convolutional neural network with transfer learning models", Machine Learning with Applications, 2021 Publication	1%
3	"Computer Vision and Image Processing", Springer Science and Business Media LLC, 2023 Publication	1%
4	Mikkili Dileep Kumar, G V Sivanarayana, D.N.V.S.L.S. Indira, M. Pruthvi Raj. "Skin cancer segmentation with the aid of multi-class dilated D-net (MD2N) framework", Multimedia Tools and Applications, 2023 Publication	1%
5	Submitted to University of Northumbria at Newcastle	1%