

SKIN CANCER CLASSIFICATION USING SKINNET

Submitted in partial fulfillment of the requirements for the award of
Bachelor of Engineering degree in Computer Science and Engineering

By

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DEPARTMENT OF COMPUTER SCIENCE AND ENGINEERING

SCHOOL OF COMPUTING

SATHYABAMA

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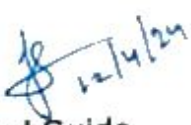
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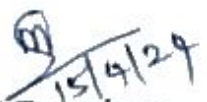
This is to certify that this Project Report is the bonafide work of **Kiruthika T (40110594)** and **Kaviya G (40110583)** who carried out the Project work entitled "**Skin Cancer Classification using SkinNet**" under my supervision from November 2023 to April 2024.

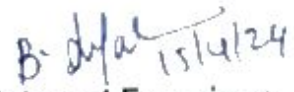

Internal Guide

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DECLARATION

I, **Kiruthika T (40110594)**, hereby declare that the Project work entitled "**SKIN CANCER CLASSIFICATION USING SKINNNET**" done by me under the guidance of **Dr. J. JESLIN SHANTHAMALAR, M.E., Ph.D.**, is submitted in partial fulfillment of the requirements for the award of Bachelor of Engineering degree in **Computer Science and Engineering**.

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ABSTRACT

Skin cancer poses a significant global health challenge, characterized by the abnormal growth of skin cells, emphasizing the urgent need for accurate lesion detection to facilitate timely medical intervention. Our research endeavors to address this imperative by developing an advanced classification model capable of discerning between seven specific types of skin cancer, including Melanoma, Basal cell carcinoma, and others. This ambitious undertaking, known as SkinNet, leverages a sophisticated Convolutional Neural Network (CNN) architecture meticulously designed to distinguish the diverse manifestations of skin cancer with precision.

The successful implementation of SkinNet has yielded remarkable outcomes, boasting an exceptional accuracy rate of 98% in classifying various skin cancer diseases. This groundbreaking achievement represents a significant milestone in healthcare technology, holding promising prospects for both medical practitioners and patients. By harnessing cutting-edge machine learning techniques, SkinNet showcases the potential to revolutionize the landscape of skin cancer diagnosis and treatment. These results underscore the transformative impact of advanced technologies in augmenting medical practices, offering avenues for more streamlined and effective management of skin cancer cases.

The implications of our study extend beyond mere technological advancements, signaling a paradigm shift in healthcare delivery. By integrating innovative computational methodologies like SkinNet into clinical practice, we envision a future where the diagnosis and treatment of complex medical conditions such as skin cancer are significantly enhanced. This heralds a new era in healthcare, where advanced algorithms and artificial intelligence play a pivotal role in addressing the challenges posed by intricate diseases. Ultimately, our research underscores the transformative potential of interdisciplinary collaborations between medicine and technology in advancing patient care and outcomes.

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LIST OF ABBREVIATIONS

ABBREVIATION	EXPANSION
BCC	Basal Cell Carcinoma
CNN	Convolutional Neural Network
GPU	Graphical Processing Unit

CHAPTER 1

INTRODUCTION

Human skin is the largest organ in our body which provides protection against heat, light, infections and injury. It also stores water, fat, and vitamins. The deadliest types in cancers are the Skin Cancer, since it would spread all over our body and if this not discovered and treated in the early stage. The skin consists of three distinct layers: epidermis, dermis, and hypodermis. The World Health Organization also estimated high cases of Melanoma and Non-Melanoma across the world. These begin with an inability to proliferate skin cells, resulting in acne, which can appear benign or malignant. Malignant acne disrupts the body's natural processes and can spread to other areas, posing serious health risks. Skin self-examination and skin clinical examination are the conventional methods of skin lesions detection.

However, these methods of examination are very hectic and troublesome. The method requires a lot of physical visits from patients and is also very expensive. These examinations also require specialized tools such as micro spectroscopy and laser-based tools. It requires effort to operate and a lot of training. The revolution brought by the smartphones allowed patients to share the image through the phone for the skin lesions diagnosis.

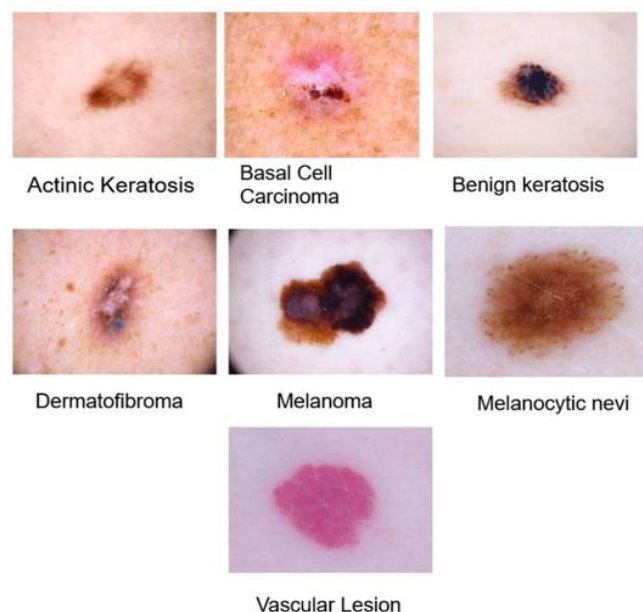


Fig. 1.1. Sample Images from Each Class

1.1 ACTINIC KERATOSES

Actinic keratoses vary in appearance. Signs and symptoms include:

- Rough, dry or scaly patch of skin, usually less than 1 inch (2.5 centimeters) in diameter.
- Flat to slightly raised patch or bump on the top layer of skin.
- In some cases, a hard, wart-like surface Color variation, including pink, red or brown.
- Itching, burning, bleeding or crusting.
- New patches or bumps on sun-exposed areas of the head, neck, hands and forearms.



Fig 1.2 Actinic Keratosis

1.2 BASAL CELL CARCINOMA

Basal cell carcinoma (BCC) is characterized by its slow and often subtle growth, making it crucial for individuals to be vigilant about any changes in their skin's appearance. Here is the signs and symptoms:

- It typically manifests as a small, shiny bump or nodule on the skin, and its growth progresses gradually, becoming more noticeable over time.
- It can lead to open sores, ulcers, or crusting, with persistent lesions requiring attention.
- Early BCC appears as raised, pink or red bumps on the skin, resembling a mole.
- It may show visible blood vessels, aiding in diagnosis.



Fig 1.3 Basal Cell Carcinoma

1.3 DERMATOFIBROMAS

Dermatofibromas tend to grow slowly. The growths typically have some defining characteristics that can aid their identification.

Key markers of a dermatofibroma are:

- Appearance: A dermatofibroma presents as a round bump that is mostly under the skin.
- Size: The normal range is about 0.5-1.5 centimeters (cm), with most lesions being 0.7-1.0 cm in diameter. The size will usually remain stable.
- Color: The growths vary in color among individuals but will generally be pink, red, gray, brown, or black.
- Location: Dermatofibromas are most common on the legs, but they sometimes appear on the arms, trunk, and, less commonly, elsewhere on the body.
- Additional symptoms: Although they are usually harmless and painless, these growths may occasionally be itchy, tender, painful, or inflamed.



Fig 1.4 Dermatofibroma

1.4 BENIGN KERATOSIS

Benign keratosis, or seborrheic keratosis, is a non-cancerous skin growth that develops gradually with age. Here are five points about how benign keratosis grows and its signs and symptoms:

- Initial signs include small, rough, or raised skin lesions, evolving in size and thickness over time.
- It appears as waxy, wart-like protrusions or flat, brownish patches with a well-defined border, often varying in color from light tan to brown or black.
- The texture and color of benign keratosis can change over time.
- Commonly found on sun-exposed skin, benign keratosis typically occurs on the face, arms, and trunk.
- It is usually symptom-free and painless. Removal may be considered for cosmetic or comfort reasons.



Fig 1.5 Benign Keratosis

1.5 MELANOMA

Melanoma can affect people of any skin tone. In people with darker skin tones, melanoma tends to occur on the palms or soles, or under the fingernails or toenails. Melanoma signs include:

- A large brownish spot with darker speckles.
- A mole that changes in color, size or feel or that bleeds.
- A small lesion with an irregular border and portions that appear red, pink, white, blue.
- A painful lesion that itches or burns.
- Dark lesions on your palms, soles, fingertips or toes, or on mucous membranes lining your mouth, nose, vagina or anus

Deep learning, a powerful subset of artificial intelligence, provides precise tools for image segmentation, and reveals the complex neural networks of the human brain. The research goal types revolve around quick and effective ways to detect skin cancer, emphasizing the critical importance of what has been lost.



Fig 1.6 Melanoma

1.6 MELANOCYTIC NEVI

Melanocytic Nevi: Understanding Characteristics and Changes:

- Steady growth during childhood and adolescence; typically harmless; may evolve over time; often reach final size by adulthood.
- Monitor mole changes: Rapid growth, shape alterations, and symptoms like itching or bleeding may indicate an evolving melanocytic nevus.
- The ABCDE rule can help in assessing moles: Asymmetry, irregular Borders, uneven or changing Colors, Diameter larger than a pencil eraser, and Evolving characteristics.



Fig 1.7 Melanocytic nevi

1.7 VASCULAR LESIONS

Understanding Vascular Lesions: Exploring the Growth, Characteristics, and Symptoms of Vascular Lesions.

- Vascular lesions grow abnormally, undergoing phases of development, stabilization, and potential regression, influenced by factors like hormones and trauma.
- It manifests with varying signs like discoloration, swelling, and discomfort, depending on type and location.



Fig 1.8 Vascular Lesion

1.8 DEEP LEARNING

Deep learning is a branch of machine learning which is completely based on artificial neural networks, as neural networks are going to mimic the human brain so deep learning is also a kind of mimic of the human brain. In deep learning, we don't need to explicitly program everything. The concept of deep learning is not new. It has been around for a couple of years now. It's hype nowadays because earlier we did not have that much processing power and a lot of data. The training time for the deep learning algorithm increases because of the usage of the very large dataset.

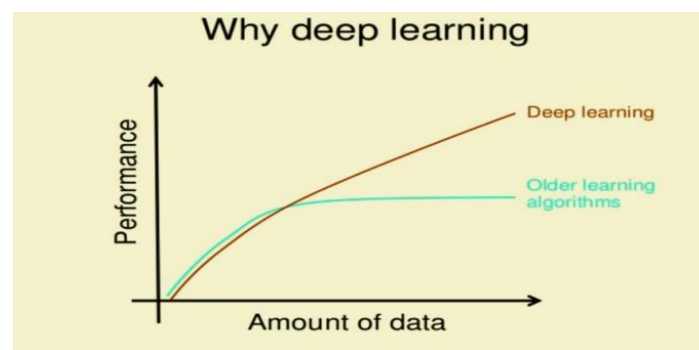


Fig: 1.9. Comparison graph

Deep learning algorithms choose their own features unlike machine learning making the prediction process easier for the end user as it does not use much pre-processing. Elaborately, a deep learning technique learns categories incrementally through its hidden layer architecture, defining low-level categories like letters first then little higher-level categories like words and then higher-level categories like sentences. A big advantage with deep learning, and a key part in understanding why it's becoming popular, is that it's powered by massive amounts of data. The "Big Data Era" of technology will provide huge amounts of opportunities for new innovations in deep learning.

CHAPTER 2

LITERATURE SURVEY

This study was conducted by C. Sinz, P. Tschandl, C. Rosendahl, B. N. Akay, G. Argenziano, et al., described by: Gourhant, J. Kreusch, et al., entitled "Accurate Diagnosis of Non-pigmented Skin Carcinomas, 1999." published in the Journal of the American Academy of Dermatology of non-pigmented skin cancer. It goes deeper into the research of effective skin philosophy for diagnosis of the disease. The comprehensive evaluation includes an investigation into the accuracy of the diagnosis, providing valuable insight into the potential of dermoscopy as a screening tool for non-pigmented skin disorders.

L. Yu, H. Chen, Q. Dou, J. Qin, P.-A. Heng gave a big boost to the industry in 2017. Their research titled "Automatic melanoma detection in dermoscopic images by ultra-deep residual mesh" focused on using ultra-deep residual mesh to detect melanoma accurately especially dermoscopy as it incorporates in-depth learning methods that contributes to research, including the increased detection of melanoma highlights its possibilities.

The publication by R. L. Siegel, K.D. Miller, and A. Jemal, titled "Cancer Statistics 2019" in A Cancer Journal for Clinicians, is a significant contribution to cancer research. Provides comprehensive and up-to-date cancer statistics for 2019, providing valuable insights for researchers, clinicians and policy makers. This project is an important model for understanding the prevalence of cancer types, and trends in various types of cancer, serving as a foundational resource for shaping strategies in cancer prevention, diagnosis, and treatment.

Ahmed Demir's 2019 research on deep learning systems for skin cancer detection is crucial for the development of the project. Their study used important biomedical data to train and test the ResNet-101 model, which is the first deep learning framework to be used in this context. A notable achievement of this study is the inclusion of two different deep learning methods in the ResNet-101 model, resulting in a multidimensional approach to skin cancer detection. This emphasizes the

complexity of the task and the importance of multiple methods of assessment for accuracy and reliability. This provides valuable insights for future research, and paves the way for increased accuracy in skin cancer detection methods in deep learning for medical applications.

In 2020, Chee Jen Ngeh conducted a observe showcasing the feasibility of going for walks computationally extensive obligations like deep studying on a Raspberry Pi. The effects indicated the potential for integration right into a value-effective scientific handheld tool.

Yunendah Nur Fu'adah 2020 proposed an automatic system used to classify the 4 types of skin cancer diseases based on digital image processing. The CNN model consists of 3 layers using 3 x 3 filters. They used Adam optimizer which exhibits most excellent overall performance in classifying pores and skin most cancers lesions and benign tumor lesions, reaching a first rate 99% accuracy, a low loss of 0.0346, and almost best precision, do not forget, and F1-score values, each near 1.

In 2020, Harikrishna Kondviti conducted a study on “Skin cancer detection using transfer learning” to screen for skin cancer using the HAM10000 dataset which is widely accepted in dermatology. Their study consumed better at recall, an important metric in medical image analysis, which ensured accurate identification of high-quality data. Neurons were also trained over a 30-year period, emphasizing the importance of optimal age determination to obtain accurate results of skin cancer by performing diagnosis.

In 2020, Nour Abuared conducted advanced research on “Skin cancer detection using VGG19 architecture and Transfer Learning techniques” in that the HAM10000 data set, which is a well-established collection of dermatology images, was used. Notably, their analysis yields the proposed method, although no specifics are provided. This is likely to involve a combination of strategies to improve skin cancer detection, including data preprocessing, model design modifications, transfer theory, and training methods -Transfer learning is a common practice to optimize pre-trained models for classification tasks.

X. Wang brought a singular technique known as the Multi-stage Attentive Skin Lesion Learning (MASLL) community, aiming to improve the class of melanoma. The MASLL network in all likelihood employs attention mechanisms across multiple stages, suggesting a complicated approach to enhance the version's functionality in correctly figuring out cancer skin lesions.

In 2021, R. Raja Subramanian conducted a landmark research on skin cancer detection, using convolutional neural network (CNN) technology. They used the popular HAM10000 data from dermatology research to get impressive results. Their CNN model demonstrated exceptional accuracy, correctly identifying skin cancer cases at an impressive rate of 83.11%, with a strong F-score of 0.82797%. Besides, the accuracy of their model was measured at 0.818642% in the detection of skin cancer in all positive cases, further confirming its reliability, and indicating that the truly positive cases have been accurately diagnosed. These findings highlight the possibilities of CNNs as a valuable tool in skin disease image analysis and skin cancer detection.

Javaid's 2021 work on machine learning applications for skin cancer screening is a big contribution. The study uses the ISIC-ISBI data set, which is renowned for its breadth and diversity of skin cancer research. This dataset forms the basis for training machine learning algorithms designed for skin cancer, and the Javaid study highlights its important role. Notably, the uniqueness of this study lies in the method it is used to train algorithms that continuously use negative data to improve accuracy and efficiency in skin cancer detection. This dynamic approach not only improves assessment accuracy but also reduces unnecessary anxiety, providing a balanced and practical approach to health research.

In 2021, Sarah Haggenmueller and colleagues suggested the functionality of CNN-based totally approaches to transform into progressive diagnostic tools (DBs). To beautify the clinical applicability of the outcomes, it's far encouraged that future comparative studies be performed in more realistic situations, making use of external Out-of-Distribution (OOD) take a look at units that represent a numerous range of ethnicities and scientific occurrences of cancer subtypes.

In 2022, Atharva Kulkarni's research on skin disease classification made significant progress in the diagnosis of skin lesions. Their new approach was to use a single convolutional neural network (CNN) and finally reveal an end-to-end training algorithm. Unlike many traditional models that rely on complex extraction and preprocessing steps, Kulkarni's CNN was designed to directly accept pixel data and disease labels as input. This approach offers a truthful and green technique to categorizing pores and skin lesions. Mixing pixel-level information and relevant disease labels in the training pipeline facilitates model understanding of skin conditions, increasing classification accuracy.

In the work conducted by Iftiaz A. Alfi in 2022, an interpretable method to melanoma pores and skin most cancers prognosis turned into brought. This method concerned making use of deep studying strategies and ensemble stacking of device studying fashions. The objective became to beautify the accuracy of cancer prognosis even as ensuring interpretability in knowledge of the model's decisions.

In the year 2022, Ioannis Kousis achieved state-of-the-art results in skin cancer detection through the utilization of a single, relatively light-weight deep gaining knowledge of version. The application of this model extended to a mobile app, demonstrating its adaptability and practical utility in real-world situations.

In these studies, Khalil Aljohani explored the identity of melanoma and the use of deep getting to know techniques implemented to cutaneous image processing. The take a look at worried trying out diverse convolutional neural community (CNN) architectures, together with DenseNet201, MobileNetV2, ResNet50V2, ResNet152V2, Xception, VGG16, VGG19, and Google Net. The overall performance of those deep mastering models turned into assessed on graphical processing units (GPUs).

In 2022, Ranpreet Kaur offered to take a look at introducing an automatic cancer classifier leveraging a deep convolutional neural network (CNN). The DCNN's architecture is meticulously crafted, incorporating multiple layers to extract features

from pores and skin photographs, ranging from low to excessive-level, in a distinctive manner. The primary goal is to acquire a precise type of malignant and benign cancer.

In this research conducted via R. Geetha Ramani in 2023, the focal point is on automated retinal picture quality evaluation for computer-aided analysis. The study introduces impactful feature extraction techniques, demonstrating the gadget's fantastic overall performance across various datasets. These findings underscore the performance and robustness of the proposed device in automating photo analysis for retinal sickness prognosis.

In 2021, S. Mohan Kumar conducted an experiment introducing an automated device for Skin Lesion Classification (SLC). This device makes use of Nonsubsampled Shearlet Transform (NSST) primarily based power functions coupled with a Support Vector Machine (SVM) classifier. The proposed technique targets to enhance the accuracy and performance of pores and skin lesion class.

In this research, Sarah Ali Alshawi (2023) delves into ensemble learning models together with Random Forest, Adaboost, Majority balloting, Boosted SVM, Boosted GMM, and Ensemble CNN to categorize cancer. The observer employs accuracy, precision, and take into account metrics to assess the overall performance across six melanoma classes via Stratified 10-fold move-validation. The findings display that Ensemble CNN excels with an accuracy of 98.67%. While ensemble fashions display commendable performance, their extended execution time and device intricacy pinpoint avenues for enhancement, particularly concerning the impact of dataset size on feature units.

Table 2.1 Comparison with Existing Works

No.	Researcher	Algorithms	Accuracy
1	L. Yu (2017)	FCRN	94.90%
2	H. K. Kondaveeti (2020)	ResNet50	90.00%
3	R Raja Subramanian (2021)	CNN	>80.00%
4	X. Wang (2021)	ResNet101 and DenseNET121	87.33%
5	A. Javaid (2021)	Random Forest	93.89%

2.1 INFERENCES FROM LITERATURE SURVEY

- The widespread use of convolutional neural networks (CNNs) in skin cancer research highlights the effectiveness of deep learning techniques to achieve greater diagnostic accuracy.
- The study highlights the importance of memory, and demonstrates the need for long-term training to improve model performance in skin cancer detection.
- The proposed strategies for improving model analysis emphasize the continued pursuit of more effective strategies to address the challenges of skin cancer detection.
- The shift from traditional methods to deep learning techniques, especially CNNs, is evident in skin cancer classification.
- Pre-trained CNN images generated from ImageNet, Exceptions and other sources are proving increasingly important for skin cancer detection in general
- Together, these findings reflect an evolving state of skin cancer detection, with a focus on integrating deep learning with the potential to improve screening accuracy in health care delivery.

2.2 OPEN PROBLEMS IN EXISTING SYSTEM

- An issue is the lack of explicitness in CNN-based models. The interpretation and interpretability of these models can be improved, especially in clinical settings where the decision-making process makes sense. Future research should focus on ways to improve the interpretability of CNNs.

- The limited availability of diverse and comprehensive data sets is an important challenge.
- Ensuring that skin cancer detection samples are robust to real-world conditions, such as changes in illumination, image quality, disease, and patient characteristics is needed.

CHAPTER 3

REQUIREMENT ANALYSIS

3.1 SYSTEM REQUIREMENTS:

Operating System : Windows 7/8/10

Processor : I3/Intel Processor

Hard Disk : 160GB

RAM : 8Gb

IDE : Jupyter Notebook/Google Colab.

Application : Python 3.6+

3.2 LIBRARIES USED:

For skin most cancers classification in Python, the applied libraries encompass:

- ★ Numpy
- ★ Tensorflow
- ★ Keras
- ★ PIL
- ★ Matplotlib
- ★ Pandas
- ★ Seaborn

3.1.1 NUMPY

- NumPy, brief for Numerical Python, is a library targeted on multidimensional array objects and consists of a set of routines for array processing.
- With NumPy, you can perform mathematical and logical operations on arrays.
- NumPy is an open-supply numerical Python library.

```
import numpy as np
```

3.1.2 TENSORFLOW

- TensorFlow stands as a freely available and open-supply software library

committed to machine studying.

- Its skills span a wide range of tasks, with a particular emphasis on schooling and inference for deep neural networks.
- TensorFlow operates as a symbolic math library, relying on facts float and differentiable programming standards.
- It helps GPU/CPU computing, permitting the same code to execute seamlessly on each architecture.
- Renowned for excessive scalability, TensorFlow excels in disbursed computation throughout machines and managing big datasets. Import TensorFlow to unlock these effective functions.

```
import tensorflow as tf
```

3.1.3 KERAS

- Keras, a broadly used Python Machine Learning library, affords a excessive-degree neural networks API that seamlessly runs on TensorFlow, CNTK, and Theano.
- Keras is mainly user-pleasant for Machine Learning novices, allowing them to without problems design and build neural networks.
- One of Keras' splendid strengths is its assist for short and simple prototyping.

```
from tensorflow import keras
```

3.1.4 PIL

- The PIL (Python Imaging Library) is a library in Python that provides extensive support for opening, manipulating, and saving various image file formats.
- It offers a wide range of image processing capabilities, including resizing, cropping, rotating, and filtering.
- The PIL library is widely used in computer vision, image analysis, and graphics applications.
- Additionally, PIL provides a simple interface for working with images in Python scripts, making it a popular choice for handling image-related tasks in

various projects.

```
from PIL import Image as pil_image
```

3.1.5 MATPLOTLIB

- Matplotlib, a versatile Python plotting library, empowers users with a diverse array of visualization options, including line charts, scatter plots, and histograms.
- Its customization features allow precise control over plot appearance, ensuring informative and visually appealing representations.
- Matplotlib's seamless integration with other Python libraries, such as NumPy and Pandas, further solidifies its position as a fundamental tool for data visualization in the Python ecosystem.

```
import matplotlib.pyplot as plt
```

3.1.6 PANDAS

- Pandas is a popular Python library on data analysis. 8
- It is directly related to Machine Learning. As all we have the dataset to be prepared before the training.
- In this case, Pandas are handy as a developed \to data extraction and preparation.
- It provides the implementation of high-level find data structures and a wide variety tool for data analysis.
- It provides many methods for groping, combining and filtering data.

```
import pandas as pd
```

3.1.7 SEABORN

- Seaborn, a Python data visualization library built on top of Matplotlib, simplifies the creation of aesthetically pleasing statistical graphics.
- It offers a high-level interface for drawing informative and attractive statistical

graphics.

- Seaborn provides easy-to-use functions for tasks like visualizing distributions, identifying patterns in data, and exploring relationships between variables.
- With its built-in themes and color palettes, Seaborn facilitates the creation of professional-looking visualizations with minimal effort.

```
import seaborn as sns
```

CHAPTER 4

DESCRIPTION OF THE PROPOSED SYSTEM

In our research efforts, we strategically chose to use the HAM10000 Diverse Dataset as the main cornerstone for training our machine learning model, which is specifically designed for skin cancer detection. This dataset is particularly noteworthy because it contains a large collection of skin sample images, covering a variety of cases and conditions. By using such a diverse dataset, we aim to enable our model to recognize a wide range of skin conditions, thereby improving its ability to accurately detect and classify different types of skin lesions greater than. To further improve the performance of our Convolutional Neural Network (CNN) model, we added a series of preprocessing techniques to our pipeline. These techniques incorporate a multi-stage approach, including data enhancement, color normalization, image enhancement, and resizing.

4.1 ARCHITECTURE DIAGRAM

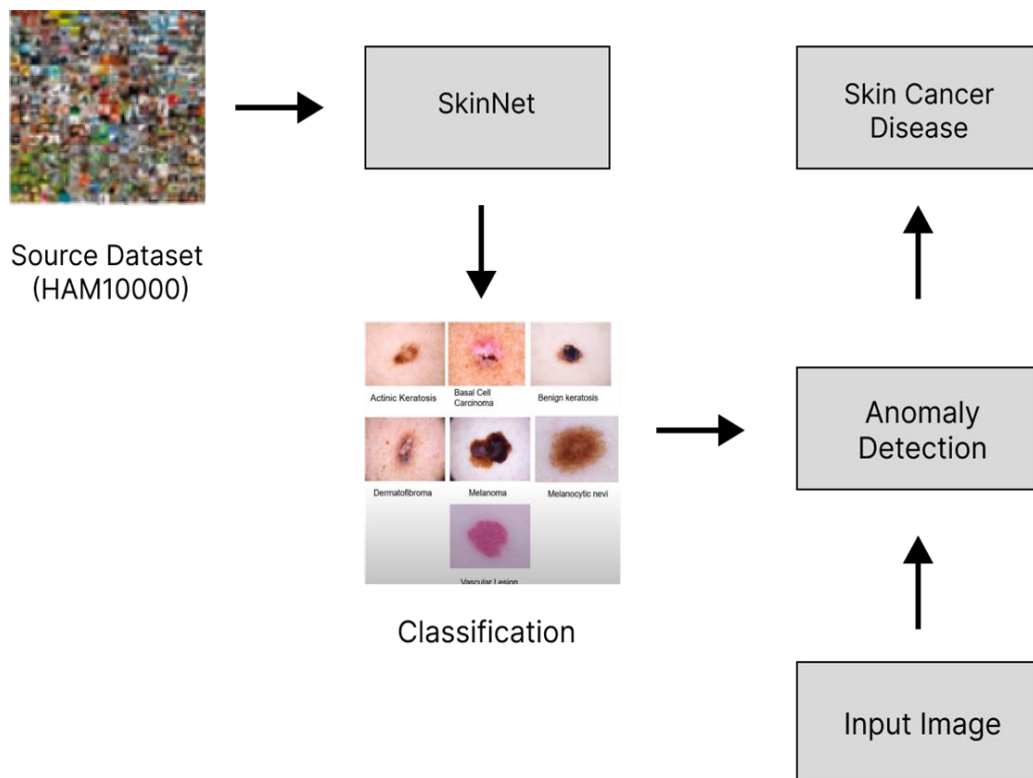


Fig. 4.1 Architecture Diagram

4.2 SELECTED METHODOLOGY OR PROCESS MODEL

The proposed architecture of skin cancer detection model, with the initial step involving data collection using the HAM10000 dataset. For this skin cancer classification, the proposed SkinNet model is introduced to train the dataset. This HAM1000 dataset is particularly noteworthy because it contains 10000 of skin cancer sample images, covering the 7 types which is Melanoma, Basal cell carcinoma, Benign keratosis-like lesions, Dermato-fibrosarcoma protuberans, Actinic keratosis, Melanocytic nevi, and Vascular lesions. Table 4.1 illustrates the classified classes of skin cancer images.

Table 4.1 Labels of Cancer Types

Label	Images
4	6705
6	1113
2	1099
1	514
0	327
5	142
3	115

Table 4.1 represents the types of skin cancer that are classified into classes which are known as labels. By using such a diverse dataset, the aim is to enable the proposed model to recognize a wide range of skin conditions, thereby improving its ability to accurately detect and classify different types of skin lesions greater than. Then we are resizing the shape of our images to train our dataset using SkinNet model. The resolution of the images size is changed to 28 x 28 as an input of the SkinNet model which consists of 26 layers with different parameters. A sequential model from Keras library which will help to make the implementation of neural networks in an easy way.

Table 4.2. Layers of SkinNet Model

Layer (type)	Output Shape	Parameter
Input Image	28, 28, 3	0
Convolution	28, 28, 32	896
Max Pooling	14, 14, 32	0
Batch Normalization	14, 14, 32	128
Convolution	14, 14, 64	18496
Convolution	14, 14, 64	36928
Max Pooling	7, 7, 64	0
Batch Normalization	7, 7, 64	256
Convolution	7, 7, 128	73856
Convolution	7, 7, 128	147584
Max Pooling	3, 3, 128	0
Batch Normalization	3, 3, 128	512
Convolution	3, 3, 256	295168
Convolution	3, 3, 256	590080
Max Pooling	1, 1, 256	0
Flatten	256	0
Dropout	256	0
Dense	256	65792
Batch Normalization	256	1024
Dense	128	32896
Batch Normalization	128	512
Dense	64	8256
Batch Normalization	64	256
Dense	32	2080
Batch Normalization	32	128
Dense	7	231
Output	7	0

4.3 PROJECT MANAGEMENT PLAN

- The First step is collecting a large number of images for different types of skin diseases.
- After that research into the medical field to study these images and based on

that developing and fine-tuning the algorithm to produce more and more accuracy.

- In construction of a DL system, selection of an appropriate DL algorithm is a crucial issue, because each algorithm has a significant effect on the accuracy of the result.
- As each algorithm has its own advantages for a specific application, there is no algorithm which is suitable for all problems.
- Developing a user-friendly portal where the user can upload images and get the result after processing.

CHAPTER 5

IMPLEMENTATION DETAILS

5.1 DEVELOPMENT AND DEPLOYMENT SETUP

The model is crafted within Jupyter Notebook, utilizing the Anaconda software which is an open-source distribution encompassing Python and other programming languages tailored for scientific computing. The application deployment is achieved through Flask, a web framework that offers essential tools and libraries, including NumPy, pandas, os, matplotlib, seaborn, shutil, tensorflow, PIL, and Keras. The Matplotlib, Seaborn libraries are used for image operations and plotting, such as graphs, charts, and tables. The Shutil and os libraries offer path and directory operations on files and the collection of files. For model building such as classification report, ROC curve, and confusion matrix, we import the torchvision and seaborn libraries. For model building such as classification report, ROC curve, and confusion matrix, we import the scikit-learn, sklearn, and seaborn libraries. The numpy and pandas are the most popularly used libraries for array processing and data analysis. Deployment of application building is done using different technologies that allow the developer to build a web application.

5.2 ALGORITHMS

In this study, a model is built from the ground up to produce superior outcomes when using Convolutional Neural Network (CNN). To reuse a previously trained model for greater accuracy, use transfer learning. In previous models they have used deep convolutional neural network models which may take days or even weeks to train on very large datasets. A way to short-cut this process is to re-use the model weights from pre-trained models that were developed for standard datasets, such as the ImageNet image recognition tasks. Top performing models can be downloaded and used directly, or integrated into a new model. Along with CNN we used the SkinNet model which we introduced in our research. Compared to traditional approaches of diagnosis, this model for skin lesions has made diagnosis and identification easier.

5.2.1 CONVOLUTIONAL NEURAL NETWORK

The convolutional layer is equipped with a filter designed to recognize specific data patterns in an image. In addition to convolutional layers, CNNs incorporate pooling and classification layers, enabling efficient reduction of high dimensionality without information loss. A small grid of parameters known as a kernel, serving as an optimizable feature extractor, is applied at each image position. This adaptability makes CNNs highly efficient in image processing, as features can be identified anywhere in the image. As layers feed their output into the next, extracted features progressively become more complex. The optimization process, involving parameters like kernels, is termed training, aiming to minimize the difference between outputs and ground truth labels through techniques like backpropagation and gradient descent.

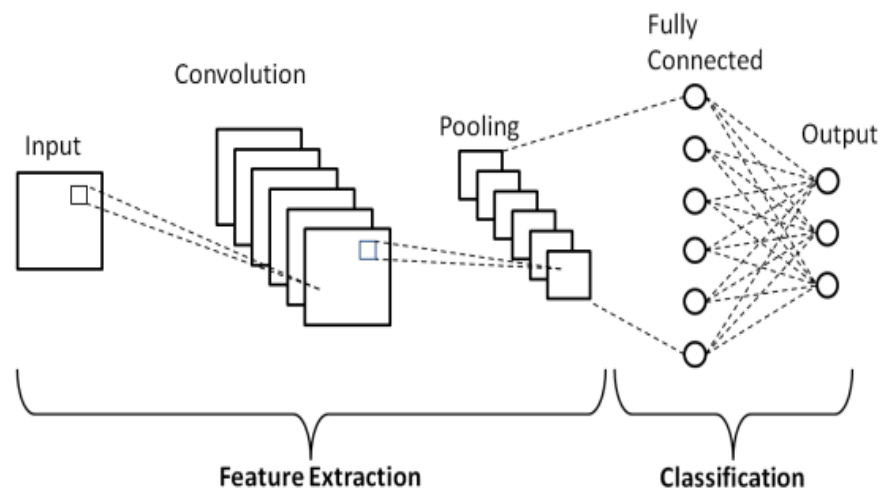


Fig 5.1 Convolutional Neural Network

A CNN's architecture comprises building blocks such as convolution layers, pooling layers (e.g., max pooling), and fully connected (FC) layers. Performance under specific kernels and weights is evaluated using a loss function during forward propagation on a training dataset. Learnable parameters, such as kernels and weights, are then updated based on the loss value through backpropagation using the gradient descent optimization algorithm, often with rectified linear units (ReLU).

The CNN architecture involves stacking several building blocks, including

convolution layers, pooling layers, and fully connected layers. Typically, repetitions of convolution and pooling layers precede one or more fully connected layers. The transformation of input data into output through these layers is termed forward propagation. While the convolution and pooling operations discussed are for 2D-CNN, similar operations can be applied to three-dimensional (3D)-CNN.

Convolutional Layer:

Our methodology initiates with a vital convolutional operation, utilizing feature detectors as filters in the neural network. This operation, central to Convolutional Neural Networks (CNNs), is essential for tasks like image analysis and feature extraction. It condenses pixels within its receptive field into a single value, efficiently reducing image size and consolidating information into a concise vector, forming the output of the convolutional layer.

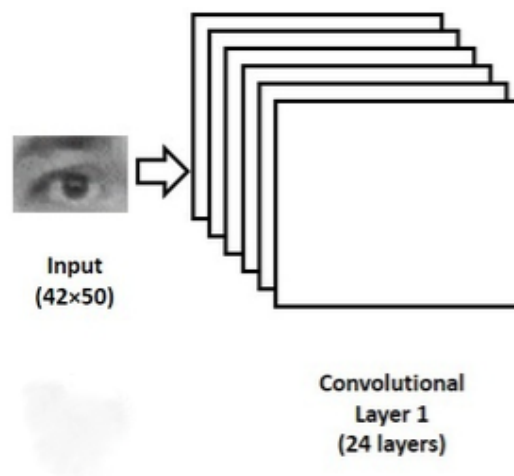


Fig 5.2 Convolution Operation

ReLU Layer:

In the ReLU layer, feature maps undergo an activation function, specifically a rectifier function. This function returns 0 for values less than 0 and the input value otherwise. This non-linear activation, in contrast to sigmoidal functions, prevents exponential computation growth in neural networks.

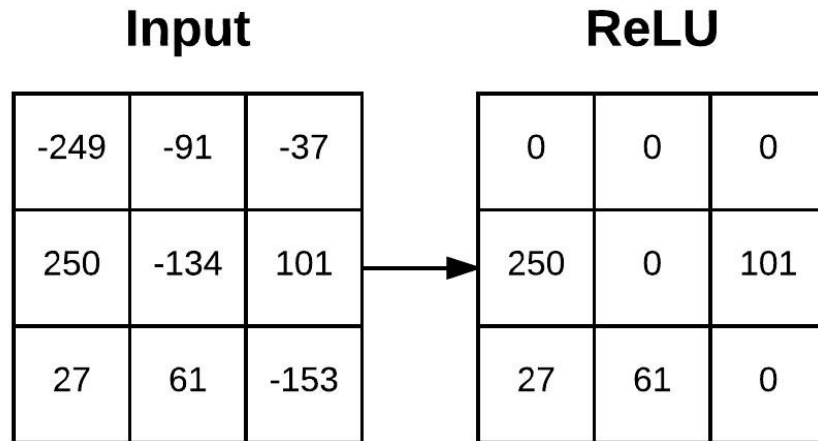


Fig 5.3 ReLU Layer

Pooling Layer:

A pooling layer provides a typical downsampling operation which reduces the in-plane dimensionality of the feature maps in order to introduce a translation invariance to small shifts and distortions, and decrease the number of subsequent learnable parameters. It is of note that there is no learnable parameter in any of the pooling layers, whereas filter size, stride, and padding are hyperparameters in pooling operations, similar to convolution operations.



Fig 5.4 Pooling Layer

5.3 MODEL BUILDING

Various methods are employed in predictive modeling to develop statistical models that forecast future behavior using input from test data. Model building includes the following main tasks: Training and testing. In This Phase we will train the model using the dataset that we have pre-processed. The data set is divided into a training set and a testing set. 25% for testing and 75% for training. Once the data is fed into the model, it analyzes the patterns, it considers a portion of the image in respect to the background or surroundings; this process is crucial for any image classification, obtained object or area with background gives feature extraction and make the decisions. The next task, evaluation of Model, high-level choices like the number, size, and kind of layers number of epochs are included in this. Every epoch displays the accuracy and loss for both the training and validation datasets. Save the model, after evaluating the model, the accuracy obtained is 95% achieved through the proposed SkinNet model.

5.4 APPLICATION BUILDING

When the SkinNet model is created, we will be combining it to a web application so that users can also use it to predict the output without coding. In the web application, the user gives the input image and gets the predictions. This section has the following tasks: Building HTML Pages, Building server-side script.

CHAPTER 6

RESULTS AND DISCUSSION

6.1 PRESENTATION OF FINDINGS

In this research, the training dataset 75% of the images and the testing dataset with the remaining 25% are applied for testing the SkinNet model. The dataset encompasses 7 distinct classes, namely Melanoma, Basal cell carcinoma, Squamous cell carcinoma, Dermatofibroma, Actinic Keratosis, Benign keratosis lesions, and Vascular lesions. The SkinNet model demonstrates an accuracy of 98% in classifying the skin cancers.

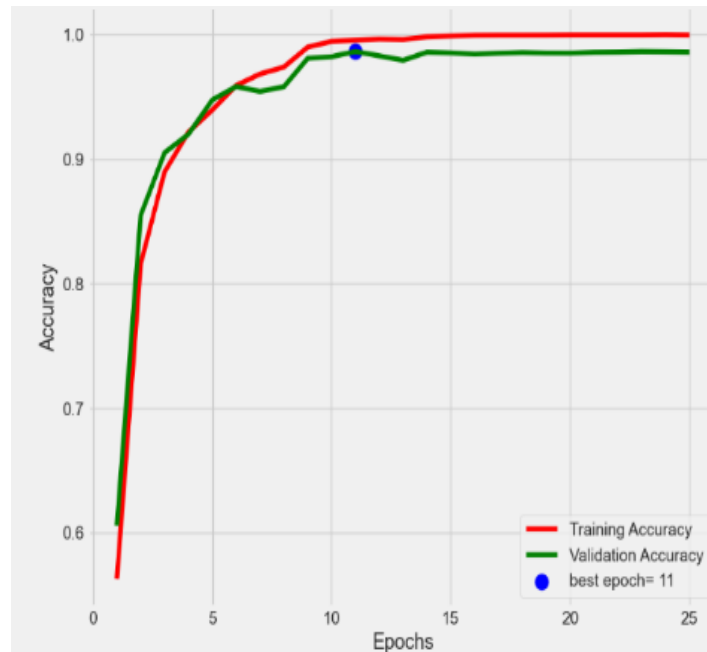


Fig: 6.1 Model Accuracy

In Fig. 6.1, the validation accuracy of skin most cancers types is depicted, showcasing the effects of Convolutional Neural Networks (CNN) implementation. This comprehensive technique is designed to both train and determine the version's efficacy in classifying various skin conditions. The graph illustrates the education and validation loss in the skin lesion class, leveraging the capabilities of a CNN.

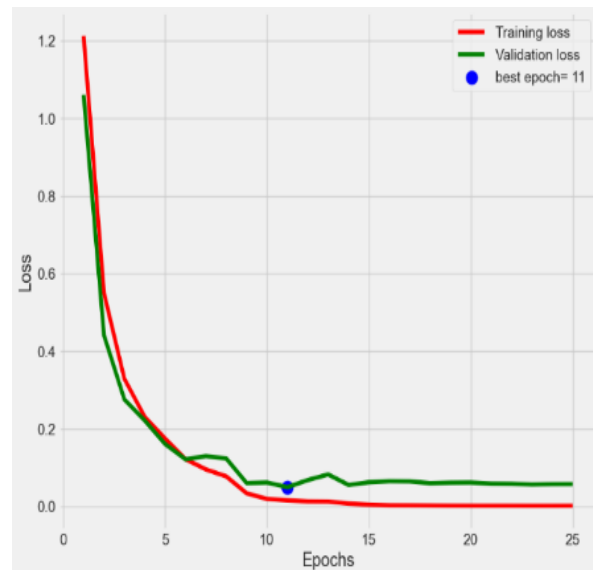


Fig: 6.2 Model Loss

Fig. 6.2. Presents the validation loss serves as a critical metric, supplying a visible knowledge of the CNN's accuracy in distinguishing numerous forms of lesions and skin cancers.

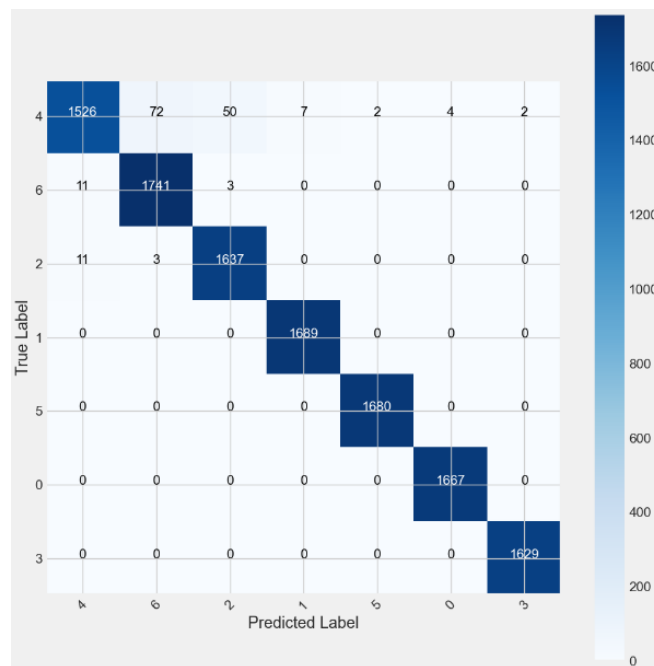


Fig: 6.3 Confusion Matrix

In context of skin cancer disease, the matrix Fig. 6.3. consists of information of the model detections for different types, and the way the ones predictions evaluate to the real classes.

Table 6.1 Output of the Project

Input	Detection	Original Name
	Actinic Keratoses	Actinic Keratoses
	Basal cell Carcinoma	Basal cell Carcinoma
	Melanocytic nevi	Benign keratosis-like lesions
	Dermatofibroma	Dermatofibroma
	Melanocytic nevi	Dermatofibroma
	Melanocytic nevi	Melanocytic nevi
	Melanoma	Melanoma
	Benign keratosis-like lesions	Vascular lesions
	Basal cell carcinoma	Benign keratosis-like lesions
	Benign keratosis-like lesions	Benign keratosis-like lesions

L. Yu's proposed approach, the depth contributes to richer feature extraction, it also introduces increased complexity and computational cost. H. K. Kondaveeti paper's dataset, the class distribution is uneven, potentially leading to biased model performance, specifically for minority training. R Raja Subramanian paper mentions implementing a multiple models and methodologies but gives result for only a subset of them. X. Wang research paper does not extensively discuss the real-world deployment issues, consisting of the interpretability of the model's choices and the potential challenges in integrating the proposed approach into scientific workflows. A. Javaid paper introduces a novel wrapper-based feature selection approach but lacks a complete exploration and comparison with alternative techniques.

Table 6.2 Comparison with Proposed work

No.	Researcher	Algorithms	Accuracy
1	L. Yu (2017)	FCRN	94.90%
2	H. K. Kondaveeti (2020)	ResNet50	90.00%
3	R Raja Subramanian (2021)	CNN	>80.00%
4	X. Wang (2021)	ResNet101 and DenseNET121	87.33%
5	A. Javaid (2021)	Random Forest	93.89%
6	Proposed Work	SkinNet	98.00%

A more in-depth evaluation of various algorithms for feature selection is important to recognize their various influences on classification performance.

CHAPTER 7

CONCLUSION

7.1 CONCLUSION

The development of this project accomplished a big fulfillment via enhancing the performance of the PC application for recognizing and knowledge pictures. Specifically, the program now efficiently identifies images with an impressive accuracy of 98%. This success is a result of the efforts to enhance the program's abilities using numerous sets of images and making it smarter in recognizing distinct patterns. Additionally, this system has been made more powerful by way of using numerous datasets, which means that it could handle a much broader range of images and situations. The way the images are put together for evaluation has also been progressed, making the program even higher at understanding and deciphering the visible facts.

7.2 FUTURE WORK

In moving forward, key steps for project development include expanding the dataset, fine-tuning hyperparameters, exploring ensemble learning and transfer learning, and incorporating interpretability. Real-time deployment and continuous monitoring, along with a user-friendly interface for healthcare professionals, are critical for practical application. These measures collectively aim to evolve the project into an effective tool for skin cancer diagnosis, advancing medical imaging and healthcare technology.

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APPENDIX

A. SOURCE CODE

1. SkinNet Model

```
import os
import time
import shutil
import itertools
!pip install opencv-python
import cv2
import numpy as np
import pandas as pd
import seaborn as sns
sns.set_style('darkgrid')
import matplotlib.pyplot as plt
import tensorflow as tf
from tensorflow import keras
from tensorflow.keras.layers import Conv2D, MaxPooling2D, Flatten, Dense,
Activation, Dropout, BatchNormalization
from tensorflow.keras.models import Model, load_model, Sequential
from tensorflow.keras.preprocessing.image import ImageDataGenerator
from sklearn.metrics import confusion_matrix, classification_report
from sklearn.model_selection import train_test_split
from tensorflow.keras.optimizers import Adam, Adamax
from tensorflow.keras import regularizers
from tensorflow.keras.metrics import categorical_crossentropy
import warnings
warnings.filterwarnings("ignore")
print ('modules loaded')
data_dir = 'C:/Users/kirut/Downloads/HAM/Dataset/hmnist_28_28_RGB.csv'
data = pd.read_csv(data_dir)
data.head()
```

```

Label = data["label"]
Data = data.drop(columns=["label"])
data["label"].value_counts()
from imblearn.over_sampling import RandomOverSampler
oversample = RandomOverSampler()
Data, Label = oversample.fit_resample(Data, Label)
Data = np.array(Data).reshape(-1, 28, 28, 3)
print('Shape of Data :', Data.shape)
Label = np.array(Label)
Label
classes = {4: ('nv', 'melanocytic nevi'),
6: ('mel', 'melanoma'),
2: ('bkl', 'benign keratosis-like lesions'),
1: ('bcc', 'basal cell carcinoma'),
5: ('vasc', 'pyogenic granulomas and hemorrhage'),
0: ('akiec', 'Actinic keratoses and intraepithelial carcinomae'),
3: ('df', 'dermatofibroma')}
from sklearn.model_selection import train_test_split
X_train , X_test , y_train , y_test = train_test_split(Data , Label , test_size = 0.25 ,
random_state = 49)
print(X_train.shape)
print(y_train.shape)
print(X_test.shape)
print(y_test.shape)
from keras.utils import to_categorical
y_train = to_categorical(y_train)
y_test = to_categorical(y_test)
datagen = ImageDataGenerator(rescale=(1./255)
,rotation_range=10
,zoom_range = 0.1
,width_shift_range=0.1
,height_shift_range=0.1)
testgen = ImageDataGenerator(rescale=(1./255))
from keras.callbacks import ReduceLROnPlateau

```

```

learning_rate_reduction = ReduceLROnPlateau(monitor='val_accuracy'
, patience = 2
, verbose=1
,factor=0.5
, min_lr=0.00001)
model = keras.models.Sequential()
# Create Model Structure
model.add(keras.layers.Input(shape=[28, 28, 3]))
model.add(keras.layers.Conv2D(32, (3, 3), activation='relu', padding='same',
kernel_initializer='he_normal'))
model.add(keras.layers.MaxPooling2D())
model.add(keras.layers.BatchNormalization())
model.add(keras.layers.Conv2D(64, (3, 3), activation='relu', padding='same',
kernel_initializer='he_normal'))
model.add(keras.layers.Conv2D(64, (3, 3), activation='relu', padding='same',
kernel_initializer='he_normal'))
model.add(keras.layers.MaxPooling2D())
model.add(keras.layers.BatchNormalization())
model.add(keras.layers.Conv2D(128, (3, 3), activation='relu', padding='same',
kernel_initializer='he_normal'))
model.add(keras.layers.Conv2D(128, (3, 3), activation='relu', padding='same',
kernel_initializer='he_normal'))
model.add(keras.layers.MaxPooling2D())
model.add(keras.layers.BatchNormalization())
model.add(keras.layers.Conv2D(256, (3, 3), activation='relu', padding='same',
kernel_initializer='he_normal'))
model.add(keras.layers.Conv2D(256, (3, 3), activation='relu', padding='same',
kernel_initializer='he_normal'))
model.add(keras.layers.MaxPooling2D())
model.add(keras.layers.Flatten())
model.add(keras.layers.Dropout(rate=0.2))
model.add(keras.layers.Dense(units=256,activation='relu',
kernel_initializer='he_normal'))
model.add(keras.layers.BatchNormalization())

```

```

model.add(keras.layers.Dense(units=128, activation='relu',
kernel_initializer='he_normal'))
model.add(keras.layers.BatchNormalization())
model.add(keras.layers.Dense(units=64, activation='relu',
kernel_initializer='he_normal'))
model.add(keras.layers.BatchNormalization())
model.add(keras.layers.Dense(units=32, activation='relu',
kernel_initializer='he_normal', kernel_regularizer=keras.regularizers.L1L2()))
model.add(keras.layers.BatchNormalization())
model.add(keras.layers.Dense(units=7, activation='softmax',
kernel_initializer='glorot_uniform', name='classifier'))
model.compile(Adamax(learning_rate= 0.001), loss= 'categorical_crossentropy',
metrics= ['accuracy'])
model.summary()
history = model.fit(X_train , y_train , epochs=25 , batch_size=128,
validation_data=(X_test , y_test) , callbacks=[learning_rate_reduction])
def plot_training(hist):
tr_acc = hist.history['accuracy']
tr_loss = hist.history['loss']
val_acc = hist.history['val_accuracy']
val_loss = hist.history['val_loss']
index_loss = np.argmin(val_loss)
val_lowest = val_loss[index_loss]
index_acc = np.argmax(val_acc)
acc_highest = val_acc[index_acc]
plt.figure(figsize= (20, 8))
plt.style.use('fivethirtyeight')
Epochs = [i+1 for i in range(len(tr_acc))]
loss_label = f'best epoch= {str(index_loss + 1)}'
acc_label = f'best epoch= {str(index_acc + 1)}'
plt.subplot(1, 2, 1)
plt.plot(Epochs, tr_loss, 'r', label= 'Training loss')
plt.plot(Epochs, val_loss, 'g', label= 'Validation loss')
plt.scatter(index_loss + 1, val_lowest, s= 150, c= 'blue', label= loss_label)

```

```

plt.title('Training and Validation Loss')
plt.xlabel('Epochs')
plt.ylabel('Loss')
plt.legend()
plt.subplot(1, 2, 2)
plt.plot(Epochs, tr_acc, 'r', label= 'Training Accuracy')
plt.plot(Epochs, val_acc, 'g', label= 'Validation Accuracy')
plt.scatter(index_acc + 1 , acc_highest, s= 150, c= 'blue', label= acc_label)
plt.title('Training and Validation Accuracy')
plt.xlabel('Epochs')
plt.ylabel('Accuracy')
plt.legend()
plt.tight_layout
plt.show()
train_score = model.evaluate(X_train, y_train, verbose= 1)
test_score = model.evaluate(X_test, y_test, verbose= 1)
print("Train Loss: ", train_score[0])
print("Train Accuracy: ", train_score[1])
print('-' * 20)
print("Test Loss: ", test_score[0])
print("Test Accuracy: ", test_score[1])
y_true = np.array(y_test)
y_pred = model.predict(X_test)
y_pred = np.argmax(y_pred , axis=1)
y_true = np.argmax(y_true , axis=1)
classes_labels = []
for key in classes.keys():
    classes_labels.append(key)
print(classes_labels)
cm = cm = confusion_matrix(y_true, y_pred, labels=classes_labels)
plt.figure(figsize= (10, 10))
plt.imshow(cm, interpolation= 'nearest', cmap= plt.cm.Blues)
plt.title('Confusion Matrix')
plt.colorbar()

```

```

tick_marks = np.arange(len(classes))
plt.xticks(tick_marks, classes, rotation= 45)
plt.yticks(tick_marks, classes)
thresh = cm.max() / 2.
for i, j in itertools.product(range(cm.shape[0]), range(cm.shape[1])):
plt.text(j, i, cm[i, j], horizontalalignment= 'center', color= 'white' if cm[i, j] > thresh
else 'black')
plt.tight_layout()
plt.ylabel('True Label')
plt.xlabel('Predicted Label')
plt.show()
model.save('SkinCancerBetter.h5')

```

2. Flask Application

app.py

```

from __future__ import division, print_function
import sys
import os
import glob
import re
import numpy as np
from PIL import Image as pil_image
from tensorflow.keras.applications.imagenet_utils import preprocess_input,
decode_predictions
from tensorflow.keras.models import Model , load_model
import keras.utils as image
from flask import Flask, redirect, url_for, request, render_template
from werkzeug.utils import secure_filename
from gevent.pywsgi import WSGIServer
app = Flask(__name__)
Model= load_model('SkinCancer.h5')
lesion_classes_dict = {0 : 'Actinic keratoses', 1 : 'Basal cell carcinoma', 2 : 'Benign
keratosis-like lesions ', 3 : 'Dermatofibroma', 4 : 'Melanocytic nevi', 5 : 'Vascular

```

```

lesions', 6 : 'Melanoma'}
def model_predict(img_path, Model):
    img = image.load_img(img_path, target_size=(28,28,3))
    #img = np.asarray(pil_image.open('img').resize((120,90)))
    #x = np.asarray(img.tolist())
    x = image.img_to_array(img)
    x = np.expand_dims(x, axis=0)
    preds = Model.predict(x)
    return preds
@app.route('/', methods=['GET'])
def index():
    # Main page
    return render_template('index.html')
@app.route('/predict', methods=['GET', 'POST'])
def upload():
    if request.method == 'POST':
        # Get the file from post request
        f = request.files['file']
        # Save the file to ./uploads
        basepath = os.path.dirname(__file__)
        file_path = os.path.join(
            basepath, 'uploads', secure_filename(f.filename))
        f.save(file_path)
        # Make prediction
        preds = model_predict(file_path, Model)
        # Process your result for human
        pred_class = preds.argmax(axis=-1) # Simple argmax
        #pred_class = decode_predictions(preds, top=1)
        pr = lesion_classes_dict[pred_class[0]]
        result =str(pr)
        return result
    return None
if __name__ == '__main__':
    app.run(debug=True)

```

index.html

```
{% extends "base.html" %} {% block content %}
<h2>Skin Cancer Classification</h2>
<h6>Choose a file and click on Predict to classify the type of Skin Cancer</h6>
<div>
<form id="upload-file" method="post" enctype="multipart/form-data">
<label for="imageUpload" class="upload-label"> Choose... </label>
<input
type="file"
name="file"
id="imageUpload"
accept=".png, .jpg, .jpeg"
/>
</form>
<div class="image-section" style="display: none">
<div class="img-preview">
<div id="imagePreview"></div>
</div>
<div>
<button type="button" class="btn btn-primary btn-lg" id="btn-predict">
Predict!
</button>
</div>
</div>
<div class="loader" style="display: none"></div>
<h3 id="result">
<span> </span>
</h3>
</div>
{% endblock %}
```

main.css

```
.img-preview {width: 256px; height: 256px; position: relative; border: 5px solid
#F8F8F8; box-shadow: 0px 2px 4px 0px rgba(0, 0, 0, 0.1); margin-top: 1em;
margin-bottom: 1em; }
.img-preview>div {width: 100%;
height: 100%; background-size: 256px 256px; background-repeat: no-repeat;
background-position: center;
}
input[type="file"] {
display: none;
}
.upload-label{
display: inline-block;
padding: 12px 30px;
background: #39D2B4;
color: #fff;
font-size: 1em;
transition: all .4s;
cursor: pointer;
}
.upload-label:hover{
background: #34495E;
color: #39D2B4;
}
.loader {
border: 8px solid #f3f3f3; /* Light grey */
border-top: 8px solid #3498db; /* Blue */
border-radius: 50%;
width: 50px;
height: 50px;
animation: spin 1s linear infinite;
}
@keyframes spin {
```

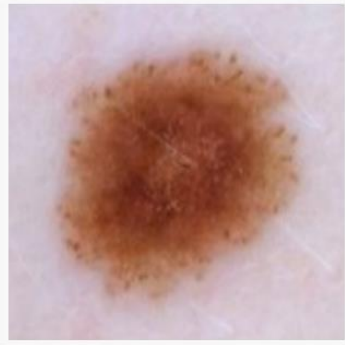
```
0% { transform: rotate(0deg); }  
100% { transform: rotate(360deg); }  
}
```

B. SCREENSHOTS

Skin Cancer

Choose a file and click on Predict to classify the type of Skin Cancer

Choose...



Result: Melanocytic nevi



Result : Actinic Keratoses



Result : Basal cell Carcinoma



Result : Benign Keratosis-like Lesions



Result : Dermatofibroma



Result : Vascular Lesions