ENHANCING HUMAN SKIN CANCER CLASSIFICATION USING DEEP LEARNING

A PROJECT REPORT

Submitted by

LOGESH R	**813820104303**
THIRISHA HELEN J	**813820104112**
SHALINI A	**813820104096**
SONALAKSHME S	**813820104103**

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ANNA UNIVERSITY : CHENNAI 600 025

BONAFIDE CERTIFICATE

Certified that this project report **" ENHANCING HUMAN SKIN CANCER CLASSIFICATION USING DEEP LEARNING "** is the bonafide work of **"R. LOGESH (813820104303), J. THIRISHA HELEN (813820104112), A. SHALINI (813820104096), S. SONALAKSHME (813820104103)",** who carried out the project work under our supervision.

SIGNATURE	**SIGNATURE**
Dr. V.Punitha, M.E. , Ph.D.	Dr. P.D.Sheba, M.E. , Ph.D.
HEAD OF THE DEPARTMENT	**SUPERVISOR**
PROFESSOR & HEAD	PROFESSOR
Department of CSE	Department of CSE
Saranathan College of Engineering	Saranathan College of Engineering
Panjapur, Tiruchirapalli - 620012.	Panjapur, Tiruchirapalli - 620012.

VIVA-VOCE EXAMINATION

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The Viva-Voce Examination of this project work done as a part of B.E. Computer Science and Engineering was held on ………………

INTERNAL EXAMINER EXTERNAL EXAMINER

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ABSTRACT

Skin cancer is a prevalent and potentially life-threatening condition, with early detection being critical for effective treatment and patient recovery. However, manual diagnosis by dermatologists can be time consuming and subjective, highlighting the need for automated systems to assist in the diagnostic process. Hence, this project work aims to develop a sophisticated Human Skin Cancer Classification System which is capable of accurately classifying various skin cancers such as Actinic keratoses, Basal cell carcinoma, Benign keratinous- like lesions, Dermatofibroma, Melanocytic nevi, Melanoma, Vascular lesions using advanced machine learning techniques. The proposed system processes the input image to predict whether the skin has been affected by skin cancer and also provides the category. The proposed system employs pattern matching and image classification using deep Learning algorithms.

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LIST OF SYMBOLS

SYMBOLS	DESCRIPTION
X	Input data, typically representing images of skin lesions.
Y	Output labels, indicating the ground truth diagnosis or skin cancer classification.
x	A single input instance (image) from the dataset.
y	Corresponding label for the input instance
D	The dataset containing pairs of input images and their corresponding labels.
Θ	Parameters of the deep learning model, including weights and baises.
fe(x)	The prediction function of the deep learning model parameterized by x.
L	Loss function, measuring the discrepancy between predicted labels and ground truth labels.
^y	Predicted label for input x produced by the model.
ytrue	True label for input x from the dataset.
L	Gradient of the loss function.
α	Learning rate, a hyperparameter controlling the step size of the parameter updates during optimization.
Z	Intermediate representations or activations produced by the ayers of the deep learning model.
A	Activation function applied element-wise to intermediate representations.
W	Weight matrix connecting neurons in consecutive layers of the neural network.

b	Bias vector added to the weighted sum of inputs in each layer.
σ	Standard deviation or scale parameter in certain layers, such as normalization layers.
μ	Mean parameter in normalization layers.
ϵ	Small constant added for numerical stability, often used in normalization

LIST OF ABBREVIATIONS

ABBREVIATIONS	DESCRIPTION
CNN	Convolutional Neural Network
DL	Deep Learning
ICA	Image Classification Algorithm
FE	Feature Extraction
DS	Dataset
RSM	Random Search Method
FCN	Fully Convolutional Network
GPU	Graphics Processing Unit
CPU	Central Processing Unit
ReLU	Rectified Linear Unit

CHAPTER 1

INTRODUCTION

1.1 SKIN CANCER DETECTION

The skin is one of the largest organs in the human body and regulates body temperature in addition to shielding the body from extreme heat and light. Additionally, it is used to store water and fat. Skin cancer is one of the most prevalent and potentially life- threatening diseases globally, with its incidence steadily rising over the past few decades. Early detection and accurate classification of skin lesions are crucial for effective treatment and improved patient outcomes. The various types of skin cancer include Actinic keratoses, Basal cell carcinoma, Benign keratinous-like lesions, Dermatofibroma, Melanocytic nevi, Melanoma, Vascular lesions. Skin cancer poses a growing challenge worldwide necessitating the development of efficient methods for early detection and classification. Traditionally, dermatologists rely on manual examination of skin lesions, which can be time-consuming and subjective. This approach is prone to human error and variability, leading to inconsistencies in diagnosis and potentially delayed treatment. Factors contributing to skin include prolonged sun sun exposure, history of sunburns, fair complexion, genetic predisposition, and tanning bed usage. Prevention strategies emphasize sun safety practices such as sunscreen application, wearing protective clothing, seeking shade, and avoiding tanning beds. Early detection plays a crucial role in successful treatment outcomes. Regular skin self-examinations and annual dermatologist visits aid in identifying suspicious lesions promptly, enabling timely intervention. Treatment modalities vary depending on cancer type and stage , ranging from surgical excision and radiation therapy to chemotherapy and targeted therapy. Through comprehensive Prevention efforts and early detection initiatives, the burden of skin can be significantly mitigated.

1.2 IMAGE PROCESSING ALGORITHMS FOR SKIN CANCER DETECTION

In recent years, advancements in technology have paved the way for automated systems to assist in skin cancer detection. Image processing algorithms have been developed to analyze dermatoscopic images, extracting features such as color, texture, and shape to aid in diagnosis. While these algorithms offer the advantage of objectivity and efficiency, they may still struggle with complex cases and subtle features, leading to potential misdiagnosis or false positives. Through sophisticated algorithms, image processing techniques can enhance image quality, segment lesions from surrounding tissue, and extract valuable information regarding lesion morphology, texture, and color. These extracted features serve as input to machine learning models, which are trained to predict the likelihood of skin cancer based on characteristic patterns present in the images. By harnessing the power of image processing, healthcare professionals can augment their diagnostic capabilities, enabling earlier detection and intervention for individuals at risk of developing skin cancer. This integration of technology not only enhances clinical decision-making but also holds promise for improving patient outcomes and reducing the burden of skin cancer on healthcare systems.

A comprehensive image processing algorithm for skin cancer detection involves several key steps. Initially, the algorithm preprocesses the input image, enhancing contrast, reducing noise, and standardizing illumination. Next, it employs segmentation techniques to isolate the suspicious regions within the image. Feature extraction follows, where relevant attributes such as color, texture, and shape are quantified from the segmented regions. These features are then utilized in a classification model, often based on machine learning algorithms, to discriminate between benign and malignant lesions.

The algorithm should be trained on a diverse dataset of annotated skin images to ensure robustness and accuracy. Finally, post-processing steps such as morphological operations and boundary refinement may be applied to refine the detected regions. Through this systematic approach, the algorithm can assist in early and accurate detection of skin cancer, aiding healthcare professionals in timely intervention and treatment.

1.3 MACHINE LEARNING FOR SKIN CANCER DETECTION

Machine learning algorithms have been employed in skin cancer detection, leveraging large datasets to train models capable of identifying patterns indicative of malignancy. However, traditional machine learning approaches often require manual feature extraction, limiting their ability to capture subtle nuances in the data. Additionally, these models may lack the flexibility to adapt to new or unseen cases, leading to reduced accuracy in real-world applications. Machine learning has emerged as a powerful tool for skin cancer detection, leveraging computational algorithms to analyze vast amounts of data and assist in the early diagnosis of skin lesions. By training models on diverse datasets containing labeled images of benign and malignant lesions, machine learning algorithms can learn to recognize patterns and features indicative of skin cancer. Supervised learning techniques such as support vector machines (SVM), convolutional neural networks (CNNs), and ensemble methods have demonstrated remarkable success in accurately distinguishing between different types of skin lesions and predicting their likelihood of malignancy. These models can analyze various aspects of lesion morphology, texture, and color, enabling healthcare professionals to make more informed decisions and prioritize individuals at higher risk for further evaluation or treatment.

Machine learning for skin cancer detection not only enhances diagnostic accuracy but also holds promise for streamlining screening processes, improving patient outcomes, and ultimately reducing the morbidity and mortality associated with this prevalent disease.

1.4 DEEP LEARNING FOR SKIN CANCER DETECTION

Unlike traditional machine learning methods, deep learning algorithms can automatically learn intricate patterns directly from raw data, such as dermatoscopic images, without the need for manual feature extraction. This ability allows deep learning models to capture subtle visual features that indicate skin cancer, leading to more accurate and reliable diagnosis. Furthermore, the flexibility and adaptability of deep learning algorithms make them well-suited for the diverse and heterogeneous nature of skin lesions, enhancing their performance in real-world scenarios. By harnessing the power of deep learning, researchers aim to develop robust and efficient systems for malignancy, such as asymmetry, border irregularity, and color variation, which may be challenging for traditional machine learning algorithms to extract manually. Moreover, deep learning models can adapt to complex and heterogeneous datasets, potentially improving accuracy and generalization performance. Consequently, researchers and practitioners turn to deep learning techniques for skin cancer prediction to leverage their capacity for automatic feature learning and robust performance on image-based tasks.

The innovative system proposed in this project work seamlessly integrates pattern matching and image classification algorithms to revolutionize the diagnosis process. This system begins with user input of an image, the system efficiently processes it through a pre-trained dataset, extracting crucial features like edges and shapes.

These features are then meticulously matched with seven categories of skin cancer data using advanced pattern matching techniques. Upon a successful match, the system delivers a precise prediction percentage and classifies the specific type of skin cancer through sophisticated image classification algorithms. By amalgamating these two powerful methodologies, the proposed system not only achieves higher accuracy but also enhances user efficiency, marking a significant leap forward from traditional diagnostic approaches.

CHAPTER 2

LITERATURE SURVEY

2.1 Skin Cancer Prediction using Deep Learning Techniques

The study conducted by Irfan T. , Rauf A. and Iqbal M.J. in 2023 presents a Skin Cancer Prediction using Deep Learning Techniques [1]. It provides a technique based on deep learning techniques to detect the cancer from skin images. Convolutional neural network-based model consisting of six layers with hidden layers is used in this work. The problem of low accuracy was addressed with the help of regularization technique and features are selected with the help of convolution method. To improve the accuracy of the model hyper parameter tuning along with model parameter tuning are performed. Publicly available dataset was used in the research which contains images with cancer and normal instances. The major steps in this work included data collection, preprocessing, data cleaning, visualization, and model development. At the end a comparative analysis was performed with state-of-the-art techniques.

2.2 Skin Cancer Lesion Analysis of Carcinoma and Melanoma Using Deep Learning Model

The study conducted by Eswaran M. , B.P. and A. M. in 2023 presents a Skin Cancer Lesion Analysis of Carcinoma and Melanoma Using Deep Learning Model [2]. A skin magnifier and polarized light source are used to visualize the tumour. Weighting and data augmentation were used. In this R- CNN classifier, the Efficient Net model was used to assess the accuracy of the skin dataset.

2.3 Deep Learning Ensemble Methods for Skin Lesion Analysis towards Melanoma Detection

The study conducted by Ali R. ,Hardie R.C. , Narayanan B N. and De Silva S. presents a Deep Learning Ensemble Methods for Skin Lesion Analysis towards Melanoma Detection in 2019 [3]. In this work, the authors have proposed Convolutional Neural Network (CNN) based ensemble methods for improving the existing performance of lesion segmentation. The ensemble technique presented in this work includes VGG19-UNet, DeeplabV3+ and other preprocessing methodologies. Extensive experiments are conducted on the ISIC 2018 challenge dataset to demonstrate the efficacy of the proposed model. For evaluation, they utilized the ISIC 2018 datasets that contains 2,594 dermoscopy images with their ground truth segmentation masks.

2.4 An innovation prediction of DNA damage of melanoma skin cancer patients using deep learning

The study conducted by Ramakrishnan R. , Mohammed M.A. , Mohammed V.A. ,Logeshwaran J. present an innovation prediction of DNA damage of melanoma skin cancer patients using deep learning in 2023 [4]. In this study, they used a deep learning-based prediction model to find possible DNA damage in ndividuals with melanoma skin cancer. They created a convolutional neural network (CNN) model to forecast the DNA damage susceptibility of melanoma cancer cells using a publicly available genome sequencing dataset. This model preprocesses the genomic data, extracts features, and categorizes them. Comparing the results of their CNN model with those of a traditional logistic regression model, they find that their CNN reported superior performance in identifying differences between healthy and cancerous samples. The authors suggested that this model can be used to augment the standard clinical diagnosis of melanoma, which only uses visual assessment and histology.

2.5 Implementation of Convolutional Neural Networks deep learning approach to Classify Melanoma Skin Cancer

The study conducted by Afroz A. , Zia R. , Noor S. , Garcia A.O. , Shams S. and Mughal S. presents a implementation of Convolutional Neural Networks deep learning approach to Classify Melanoma Skin Cancer in 2023 [5].The analysis of the dermoscopy examination's findings and comparison with medical sciences are frequently used in the manual diagnosis of melanoma cancer. Human subjectivity has a strong impact on manual detection, which renders it unreliable in some circumstances. In order to classify the outcomes of the dermoscopy test and to determine the results more precisely with a comparatively shorter amount of time, computer- assisted technology is required. Problem statement, planning, execution, and testing are the first steps in the creation of this application. To identify picture data, the research study combines deep machine learning approach using Convolutional Neural Network technique along with LeNet-5 architectural model.

2.6 Melanoma Mirage: Unmasking Skin Cancer with Deep Learning

The study conducted by Bharadwaj S.R. ,Hathwar D.K.N. , B. N. , Ramesh S. and Nair S.S. presents in 2023 presents research on automated skin cancer detection using image processing and machine learning techniques [6]. This work is on melanoma, the deadliest form of skin cancer, and highlights the limitations of clinical observation. This study uses Convolutional Neural Networks (CNNs) and feature extraction to accurately classify skin cancers as malignant or benign. The proposed method achieves high detection accuracy by removing normal skin layers, extracting valuable information, and training/testing a classification system. Studies acknowledge the rising incidence of skin cancer, emphasizing the role of early detection.

2.7 Advancements in Melanoma Skin Cancer Detection Using Deep Learning: A Comprehensive Review

The study conducted by Kachare K. , Bhagat N. and Raundale P. in 2023 presents a comprehensive review of the advancements in Melanoma Skin Cancer Detection Using Deep Learning [7]. In this study, they surveyed the effectiveness of various deep-learning algorithms for Melanoma skin cancer detection. They have studied various papers and evaluated different methods on the basis of accuracy, sensitivity, specificity, preprocessing techniques used, image segmentation, image classification, and feature extraction. The findings of this study shed important light on how well various deep learning algorithms perform at melanoma skin cancer detection, which directed the creation of more efficient diagnostic tools to enhance patient outcomes.

2.8 Melanoma Classification Approach with Deep Learning-Based Feature Extraction Models

Dos Santos et al. A.R.F. presented Melanoma Classification Approach with Deep Learning-Based Feature Extraction Models in 2021 [8].This work developed a disease detection system using Alex Net and VGG- F convolutional architectures, trained with images of skin lesions to create feature descriptors, not classifiers. Other conventional descriptors of skin lesions were used to assess the quality of data obtained from the last layers of convolutional architectures. Data from all feature extraction processes were submitted to the conventional classifiers Support Vector Machine, Multilayer Perceptron, and K-Nearest Neighbour.

CHAPTER 3

PROBLEM DEFINITION

The problem of skin cancer classification involves developing an accurate and reliable system that can analyze images of skin lesions and categorize them into diffrerent types of skin cancer. This task is critical for assisting dermatologists and healthcare professionals in diagnosing skin care at an early stage, which can significantly improve patient outcomes and treatment effectiveness. The primary objective is to design and train a deep learning model capable of automatically identifying and classifying skin lesions based on visual characteristics such as color, texture, shape, and size. By using the visual characteristics, this system can identify the skin cancers such as Actinic keratoses, Basal cell carcinoma, Benign keratinouslike lesions, Dermatofibroma, Melanocytic nevi, Melanoma, Vascular lesions. Key challenges include designing an effective feature extraction, optimizing the model's performance and ensuring the model's robustness and generalization across various skin types and lesion variations. Ultimately, the goal is to develop a highly accurate and scalable skin cancer classification system using CNN that can be deployed in clinical settings to assist healthcare professionals in making timely and accurate diagnostic decisions.

CHAPTER 4

PROPOSED SYSTEM DESIGN

4.1 SYSTEM ARCHITECTURE

The Figure 4.1 depicts the proposed system architecture. The input image is preprocessed using various filters to highlight the features such as color, shape and texture. Then the image is passed to the proposed system wherein the features are extracted and classified using a pertained model using CNN trained with several training images. The proposed system gives as output the chances of the given input to belong to seven types of skin cancers as probability in percentage.

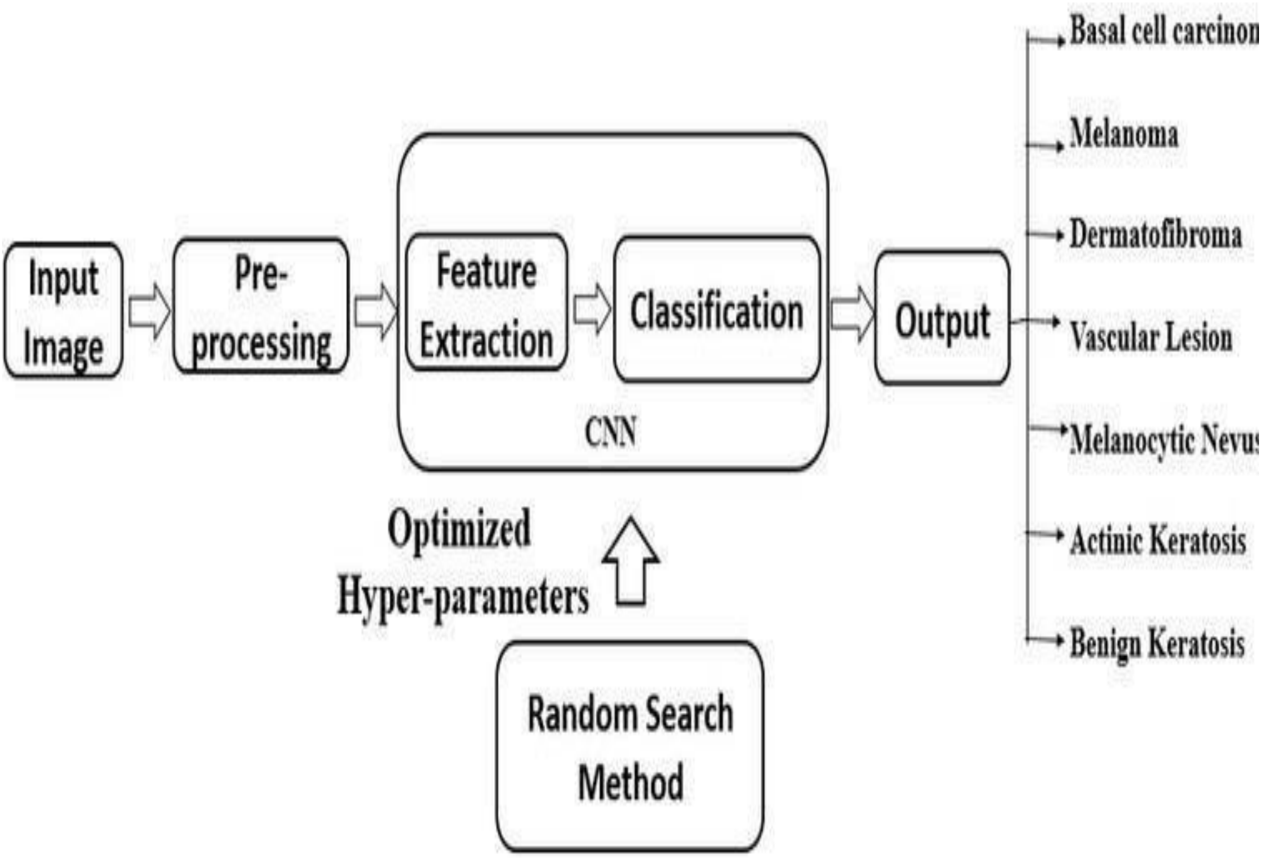

Fig 4.1 System Architecture

4.2 MODULES DESCRIPTION

4.2.1 Input image

When an input image is fed into a deep learning model for skin cancer detection, the network first extracts features from the image through a series of convolutional layers. These layers apply various filters to detect patterns and textures indicative of different types of skin lesions. For instance, they might identify irregular borders, uneven coloring, or asymmetric shapes, which are common characteristics of malignant lesions. This system can accept a skin cancer input image with a format of jpg, png and the limitation of input image size is 200 kb.

4.2.2 Image preprocessing

Image processing algorithms have been developed to analyze dermatoscopic images, extracting features such as color, texture, and shape to aid in diagnosis. While these algorithms offer the advantage of objectivity and efficiency, they may still struggle with complex cases and subtle features, leading to potential misdiagnosis or false positives. In the realm of skin cancer detection, the quality of input images greatly influences the performance of subsequent analysis algorithms. Preprocessing techniques serve to mitigate common challenges such as noise, uneven illumination, and variations in color and texture, which can obscure important features of skin lesions. By standardizing image attributes and enhancing relevant information, preprocessing lays the foundation for robust and reliable detection algorithms. The original image and the image after preprocessing are depicted in Figure 4.2a and Figure 4.2b respectively.

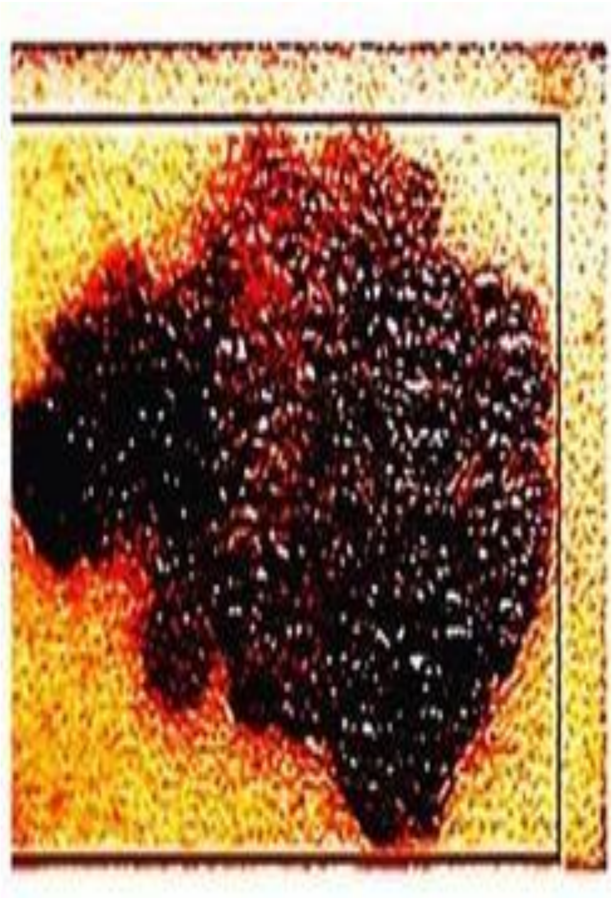

Fig 4.2a Original Image **Figure 4.2b** Preprocessed Image

4.2.3 Feature Extraction

Feature extraction involves the automatic identification and abstraction of key patterns, textures, and structures from input images. Convolutional neural networks (CNNs) are commonly employed for this purpose, as they excel at capturing hierarchical features. These features may include irregular borders, asymmetric shapes, color variations, and texture irregularities characteristic of malignant lesions. Through successive layers of convolutions, the network learns to extract increasingly abstract representations of these features. This process enables the model to effectively differentiate between benign and malignant skin lesions based on their unique visual characteristics. By automating feature extraction, deep learning facilitates more accurate and efficient skin cancer classification, potentially aiding clinicians in timely diagnosis and treatment planning.

4.2.4 Random Search Method

The random search method is a hyperparameter optimization technique employed to enhance model performance. Unlike grid search, which systematically explores a predefined set of hyperparameter combinations, random search randomly samples hyperparameter values from specified distributions. This approach efficiently explores the hyperparameter space, often yielding better results with fewer computational resources. In the context of deep learning, hyperparameters such as learning rate, batch size, and network architecture configurations significantly im pact model performance.

In the realm of skin cancer detection, the random search method serves as a valuable tool for optimizing the performance of machine learning models. This approach involves randomly sampling combinations of hyperparameters within predefined ranges to find the optimal configuration for a given model. By exploring a wide range of possibilities without following a specific pattern, the random search method efficiently navigates the hyperparameter space, potentially discovering superior configurations that may not be evident through systematic search methods. In skin cancer detection, where the choice of model architecture and hyperparameters significantly impacts the accuracy and generalization of the system, employing random search can enhance the effectiveness of machine learning algorithms. Through this method, researchers can iteratively refine their models, improving their ability to accurately diagnose skin lesions and ultimately contribute to more effective clinical decision-making.

By randomly sampling hyperparameters and evaluating model performance, the random search method helps identify optimal configurations for improving skin cancer classification accuracy. This iterative process iterates until satisfactory performance is achieved, enhancing the robustness and effectiveness of the deep learning model in diagnosing skin lesions accurately.

4.2.5 Image classification

Image classification for skin cancer using deep learning involves training a neural network to accurately categorize skin lesion images into different classes, such as Actinic keratoses, Basal cell carcinoma, Benign keratinous- like lesions, Dermatofibroma, Melanocytic nevi, Melanoma, Vascular lesions. Convolutional neural networks (CNNs) are commonly employed for this task due to their ability to automatically learn relevant features from raw pixel data. During training, the CNN learns to extract discriminative features from the input images through multiple layers of convolutions, pooling, and nonlinear activations. These learned features are then passed through fully connected layers to make predictions about the class of the skin lesion. By optimizing the network parameters using labeled data and techniques like gradient descent, the model improves its ability to correctly classify unseen skin lesion images, thus aiding dermatologists in diagnosing skin cancer accurately and efficiently.

Image classification plays a pivotal role in skin cancer detection by enabling automated analysis and diagnosis of skin lesions based on their visual characteristics. In this process, machine learning algorithms are trained to classify images into different categories, such as benign or malignant, by learning patterns and features from labeled data. Convolutional neural networks (CNNs) are commonly used for image classification tasks in skin cancer detection due to their ability to automatically extract relevant features from images. By leveraging large datasets of annotated skin lesion images, CNNs can learn to distinguish between various types of skin lesions with high accuracy. This automated classification process not only aids dermatologists in making faster and more accurate diagnoses but also holds the potential to improve access to dermatological care, particularly in underserved areas with limited access to specialized expertise. Overall, image classification serves as a powerful tool in the early detection and management of skin cancer, contributing to better patient outcomes and healthcare efficiency.

Image classification is a cornerstone technique in skin cancer classification, revolutionizing the way dermatologists diagnose and manage skin lesions. By leveraging advanced machine learning algorithms such as convolutional neural networks (CNNs), image classification enables automated analysis of skin lesion images, categorizing them into benign or malignant classes with high accuracy. This technology significantly augments dermatologists' diagnostic capabilities by providing rapid and objective assessments of skin lesions, aiding in early detection and treatment planning. Moreover, image classification systems can assist in triaging patients, prioritizing those with suspicious lesions for further evaluation, and optimizing resource allocation in healthcare settings. As a non-invasive and cost-effective approach, image classification in skin cancer classification holds immense promise in improving patient outcomes, reducing healthcare costs, and enhancing accessibility to quality dermatological care, especially in underserved communities.

4.2.6 Output

The output contains seven categories of skin cancer names along with their predicted percentage and the system generated bar chart. This output provides valuable information to dermatologists, helping them make informed decisions about diagnosis and treatment. By leveraging deep learning techniques, skin cancer classification models strive to achieve high accuracy and reliability, potentially enhancing early detection and improving patient outcomes.

CHAPTER 5

SYSTEM REQUIREMENTS

5.2.1 HARDWARE REQUIREMENTS:

i. **CPU:**

A multi-core processor with a clock speed of atleast 2.5 GHz is recommended to handle the computational load of training and testing the model.

ii. **RAM:**

A Minimum of 4GB RAM is recommended.

iii. **STORAGE:**

A Minimum of 50GB storage is recommended.

iv. **OTHER CONSIDERATIONS:**

Cooling systems and power supplies may be necessary to support the hardware and prevent overheating.

5.2.2 SOFTWARE REQUIREMENTS:

i. **OPERATING SYSTEM:**

Windows OS, mac OS or Linux.

ii. **IDE:**

Python(3.9.0)

iii. **OPENCV:** A library for computer vision and image processing, used for processing the images used.

iv. **REQUIRED LIBRARIES:**

Numpy, Pandas, Pillow, streamlit, keras, os, time, io. These are libraries used for data processing and visualization.

CHAPTER 6

SYSTEM IMPLEMENTATION

6.1 PROPOSED SYSTEM IMPLEMENTATION

6.1.1 Feature extraction

Feature extraction for skin cancer classification using deep learning involves selecting and transforming relevant characteristics from images to aid in accurate classification. This process typically includes extracting texture, color, shape, and structural features from skin lesion images. Deep learning techniques such as convolutional neural networks (CNNs) are utilized to automatically learn and extract these discriminative features. The extracted features are then fed into a classification model, such as a fully connected neural network or support vector machine, for skin cancer classification based on learned patterns and characteristics. This approach enables automated and accurate identification of skin cancer types from dermatological images.

Feature extraction in skin cancer detection involves the process of identifying and extracting relevant information from images of skin lesions to distinguish between benign and malignant cases. This process typically includes analyzing various characteristics such as asymmetry, border irregularity, color variation, and texture patterns. Techniques like edge detection, color space transformations, and texture analysis are commonly employed to extract discriminative features. These extracted features serve as input for machine learning algorithms, aiding in the development of accurate and efficient skin cancer detection systems.

Feature extraction is a critical process in skin cancer detection, pivotal for capturing relevant information from digital images of skin lesions. By quantifying distinctive characteristics such as lesion morphology, texture, and color, feature extraction enables the creation of discriminative representations that aid in distinguishing between benign and malignant lesions. Morphological features, including size, shape, and symmetry, provide insights into the overall structure of the lesion. Texture features capture patterns of pixel intensities, revealing surface characteristics like roughness and granularity. Color features quantify variations in color distribution, highlighting anomalies such as hyperpigmentation or hypopigmentation. These extracted features serve as valuable input for machine learning algorithms, empowering them to make accurate predictions and assist clinicians in early diagnosis and intervention, ultimately improving patient outcomes in skin cancer detection.

6.1.2 Image Classification using CNN

In skin cancer detection, sophisticated image classification algorithms, predominantly convolutional neural networks (CNNs), are employed due to their effectiveness in analyzing complex patterns within skin lesion images. CNNs are designed to automatically extract relevant features from these images through convolutional layers, allowing for precise discrimination between benign and malignant lesions. By training on large datasets of annotated skin images, these algorithms learn to accurately classify lesions into various cancer types, aiding in early detection and intervention.

Convolutional Neural Networks (CNNs) have revolutionized image classification tasks, including the detection of skin cancer. CNNs excel at learning hierarchical representations directly from raw image data, making them pixel by pixel, extracting features at multiple levels of abstraction through a series of convolutional, pooling, and activation layers. This hierarchical feature extraction process enables CNNs to capture intricate details and complex patterns within lesions, effectively discerning between benign and malignant cases. By training on large datasets of annotated skin lesion images, CNNs learn to generalize across different lesion types and variations in appearance, achieving impressive performance in accurately classifying unseen cases.

The ability of CNNs to automatically learn discriminative features from raw image data makes them indispensable tools in the realm of skin cancer classification, offering the potential to enhance diagnostic accuracy, expedite screening processes, and ultimately improve patient outcomes.

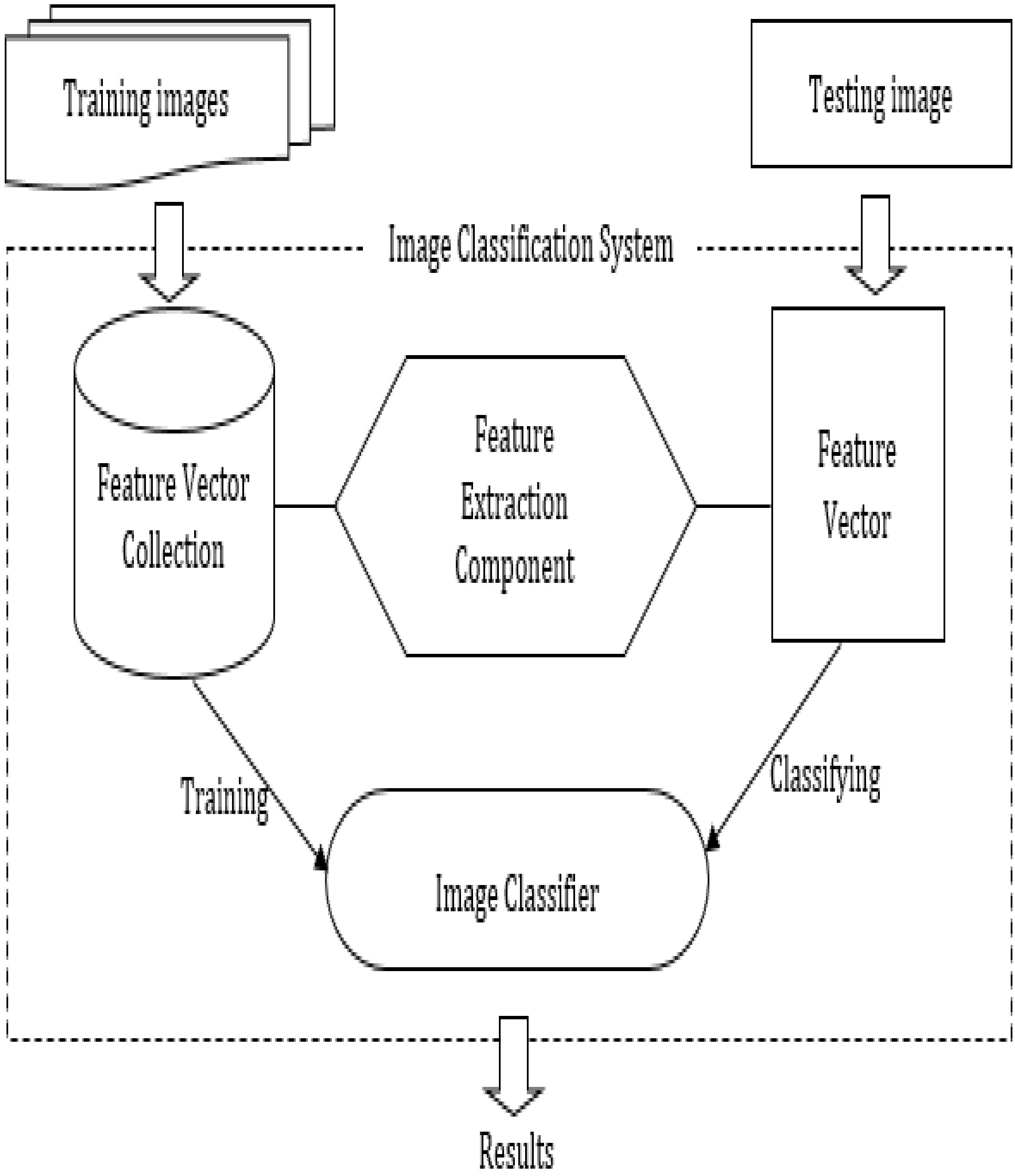

Fig 6.1.2.A Image Classification Architecture

6.2.3 Skin cancer prediction using trained model.

Skin cancer prediction using a trained model involves leveraging machine learning algorithms, such as support vector machines (SVMs), random forests, or convolutional neural networks (CNNs), that have been trained on a diverse dataset of annotated skin lesion images. Once trained, these models can analyze new, unseen images of skin lesions and predict the likelihood of malignancy based on learned patterns and features. By inputting the relevant features extracted from the lesion images, the trained model outputs a probability or classification indicating the risk of skin cancer. This predictive capability enables clinicians to prioritize individuals at higher risk for further evaluation or treatment, facilitating early diagnosis and intervention. Leveraging the power of trained models in skin cancer prediction holds promise for improving diagnostic accuracy, streamlining clinical workflows, and ultimately, enhancing patient outcomes by enabling timely and targeted interventions.

Kaggle provides an invaluable platform for developing and refining deep learning models.This Model is trained using Kaggle. When the input image of the skin cancer affected person is passed to the trained model, it matches according to the class and produces the output as probability and a bar chart.

6.2.4 Steps involved in skin cancer classification

Step 1: Upload the input image through the browse option in the system.

Step 2: After uploading the image, user will able to check the uploaded image through the show image option.

Step 3: Load the trained model for testing the input image.

Step 4: After the model is successfully loaded, the input image is passed into the trained model file for extract the features of input images such as texture, color, shape, etc.,.

Step 5: Then the extracted features are matching with the seven types of skin cancer classes.

Step 6: After matching is done, the result is to be displayed.

Step 7: The result contain seven types of skin cancer names along with the predicted percentage and the generated bar chart diagram.

6.2 RESULTS AND DISCUSSION

This work provides the result with above 85% of accuracy. After getting and processing the user input image, it displays the result that contains types of skin cancer names along with the predicted percentage and it generates the bar chart diagram. The chance in percentage that the given input image belongs to the various classes of Skin Cancer is predicted and tabulated in Table 6.1 and the same is depicted diagrammatically in a bar chart which is presented in Figure 6.1.

Table 6.1 Predicted Probability of Occurrence of Various Skin Cancers

	Classes of Skin Cancer	Probability of occurrence in %
0	Actinic keratoses	0
1	Basal cell carcinoma	1
2	Benign keratosis-like lesions	0
3	Dermatofibroma	0
4	Melanocytic levi	96
5	Melanoma	3
6	Vascular Lesions	0

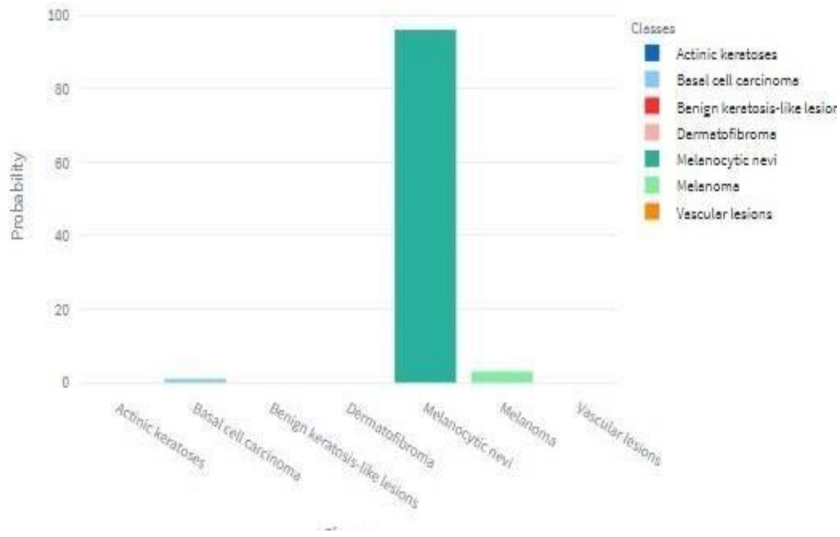

Fig 6.2.1 Probabilty of Occurrence of Various Skin cancer in %

CHAPTER 7

CONCLUSION

In conclusion, this project work demonstrates the effectiveness of deep learning in skin cancer detection, offering a powerful tool for early diagnosis. Leveraging Convolutional Neural Networks (CNNs) and advanced image processing techniques, this work has achieved high accuracy of around 85% in identification and classification of skin cancers. This approach holds significant promise for improving patient outcomes and reducing healthcare burdens. However, ongoing challenges such as dataset quality and model interpretability require further attention to realize the full potential of deep learning in dermatological diagnostics. With continued research and collaboration, deep learning-based skin cancer detection has the potential to revolutionize clinical practice and enhance public health outcomes.

APPENDICES APPENDIX - A

A.1 SCREEN SHOTS

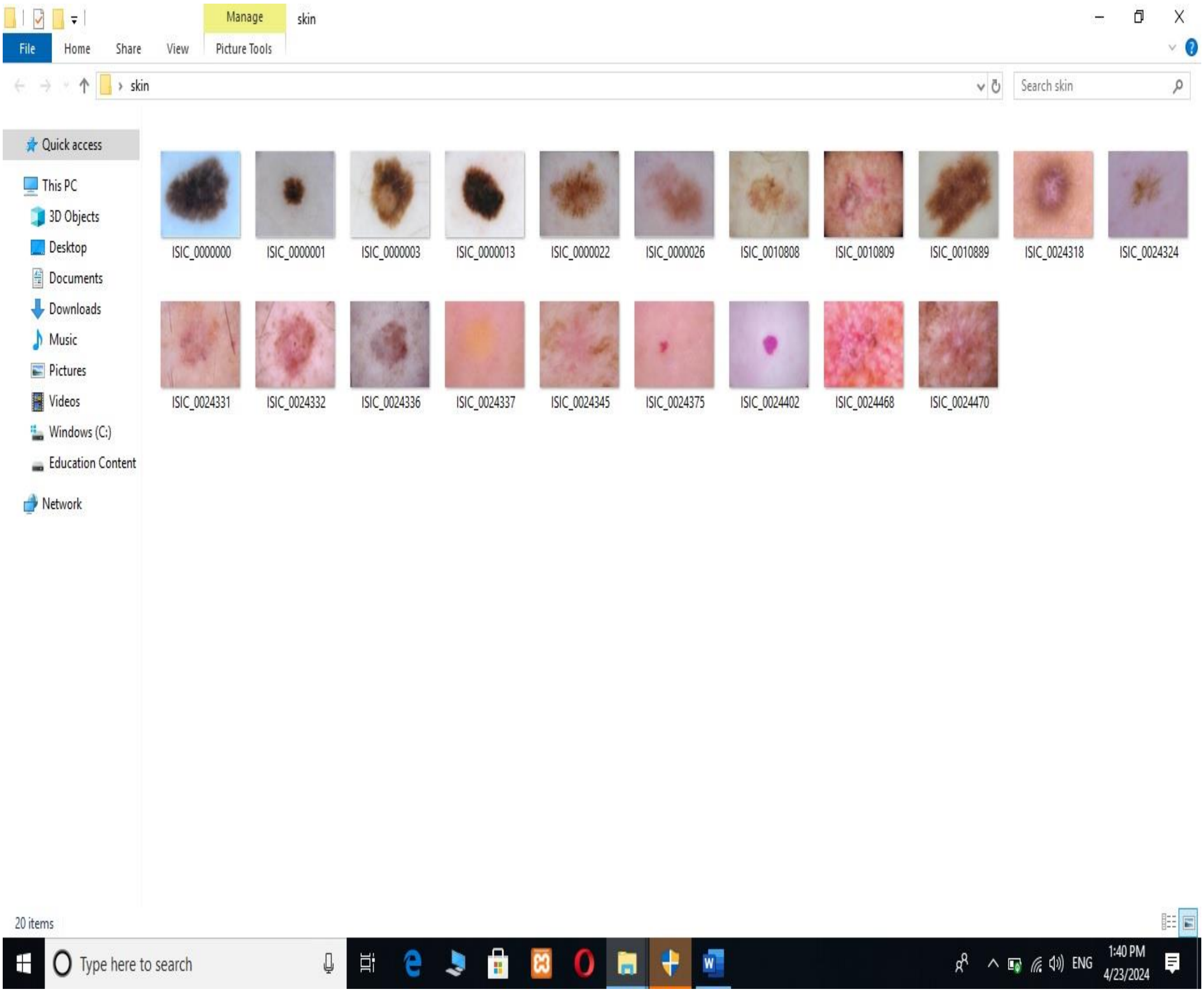

Fig A1.1 Displaying the input images

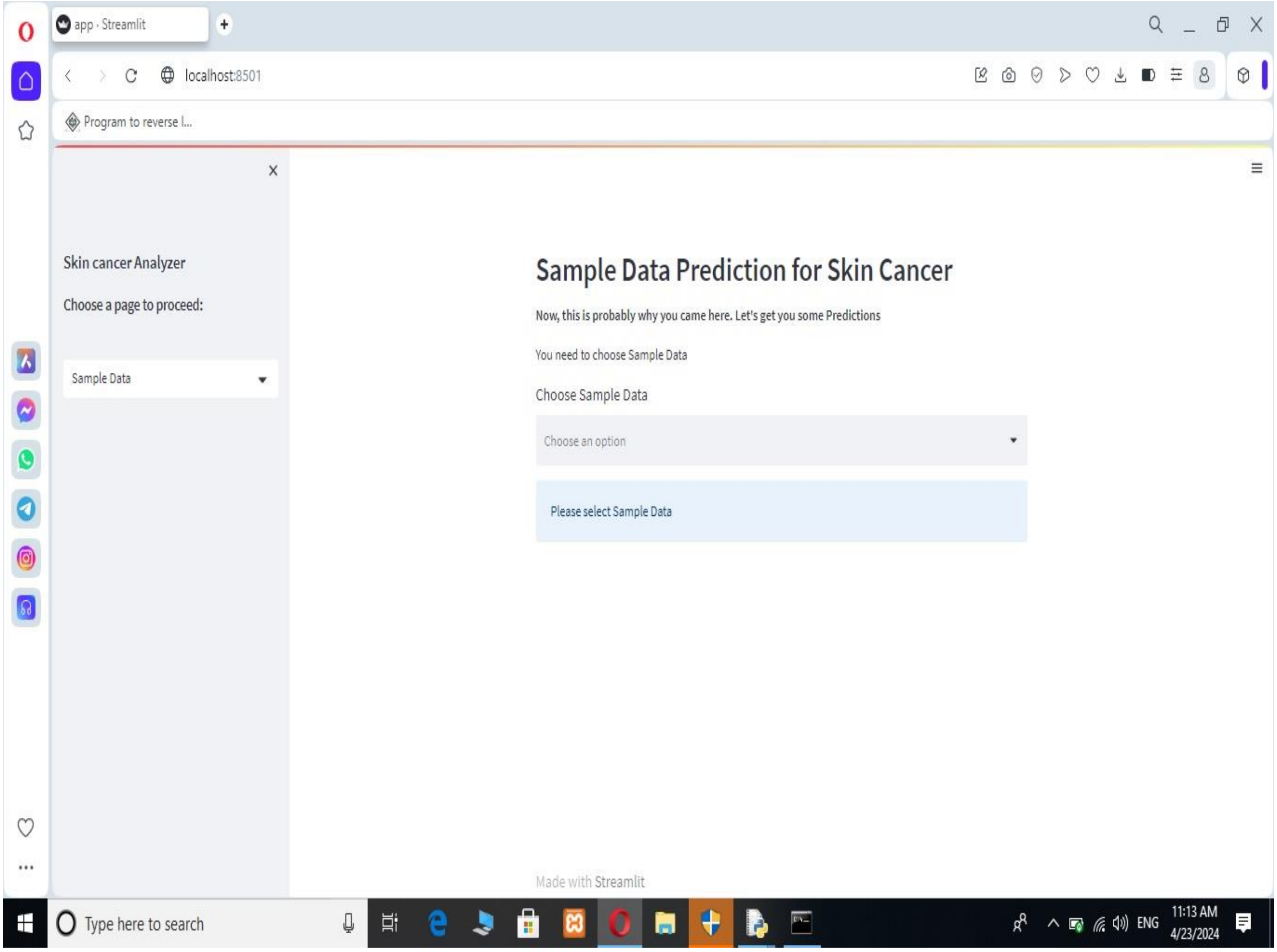

Fig A1.2 Predicting the skin cancer using sample the input image

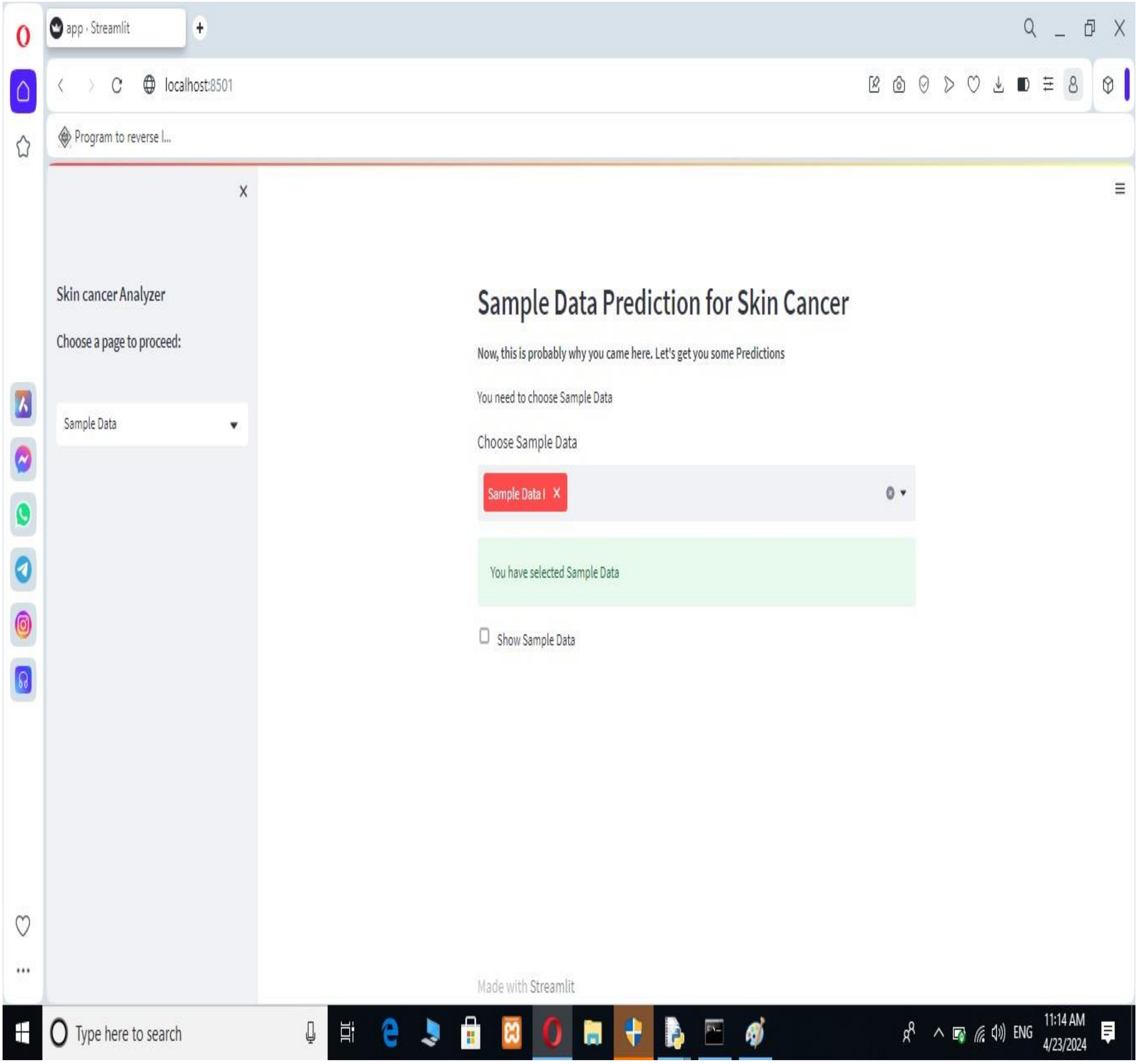

Fig A1.3 Selecting the sample input image

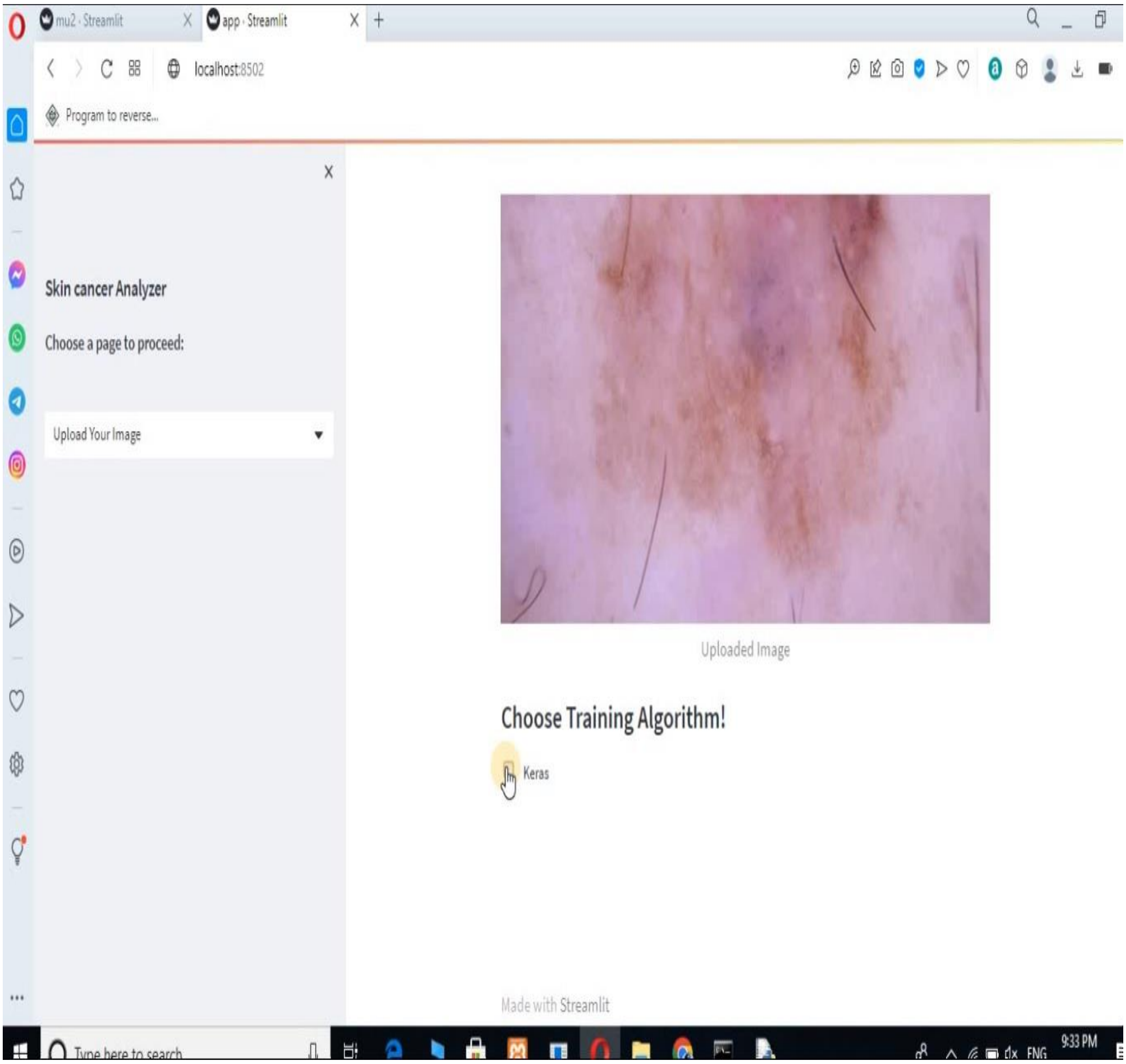

Fig A1.4 Loading the trained model

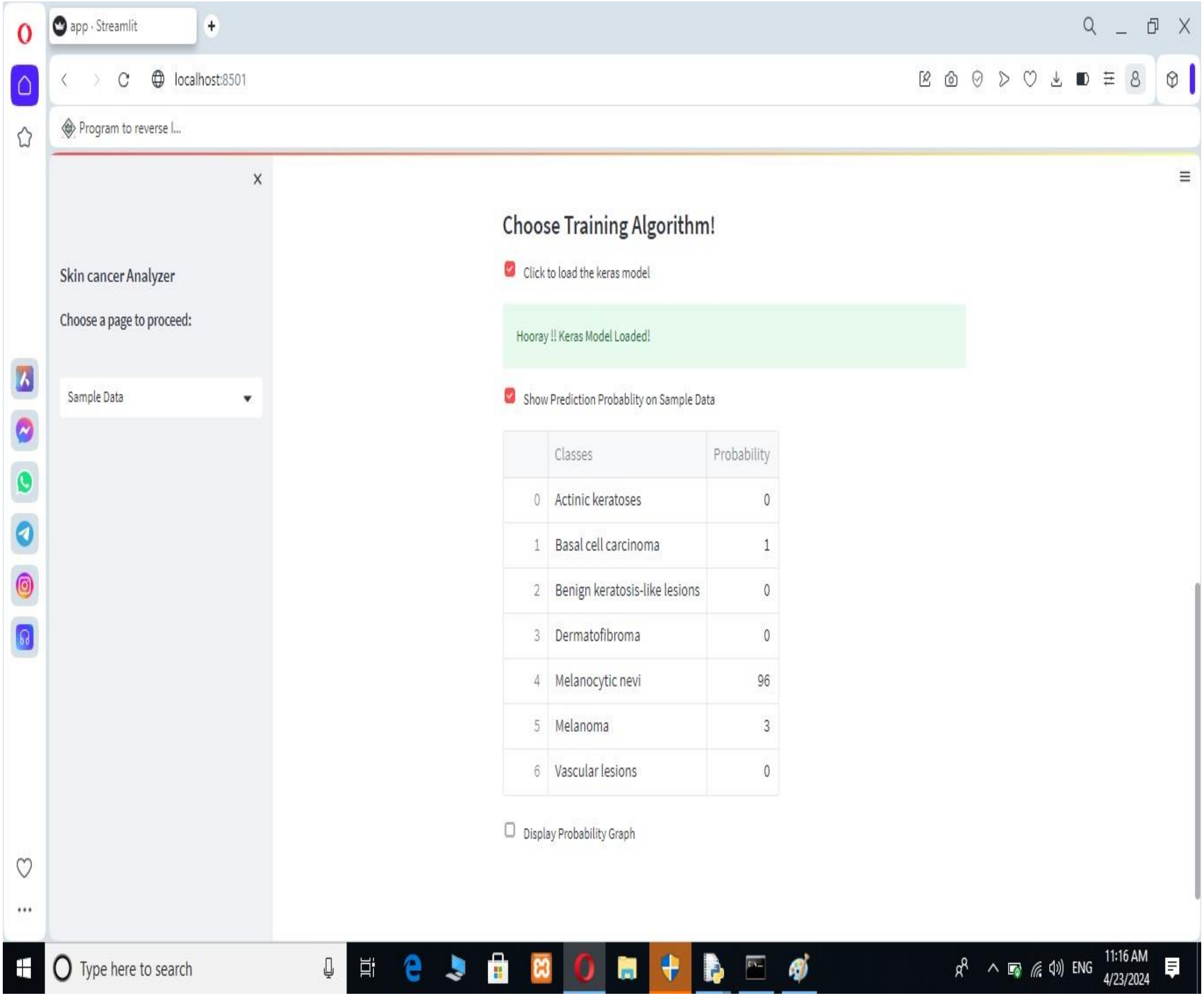

Fig A1.5 Displaying the sample data affected percentage

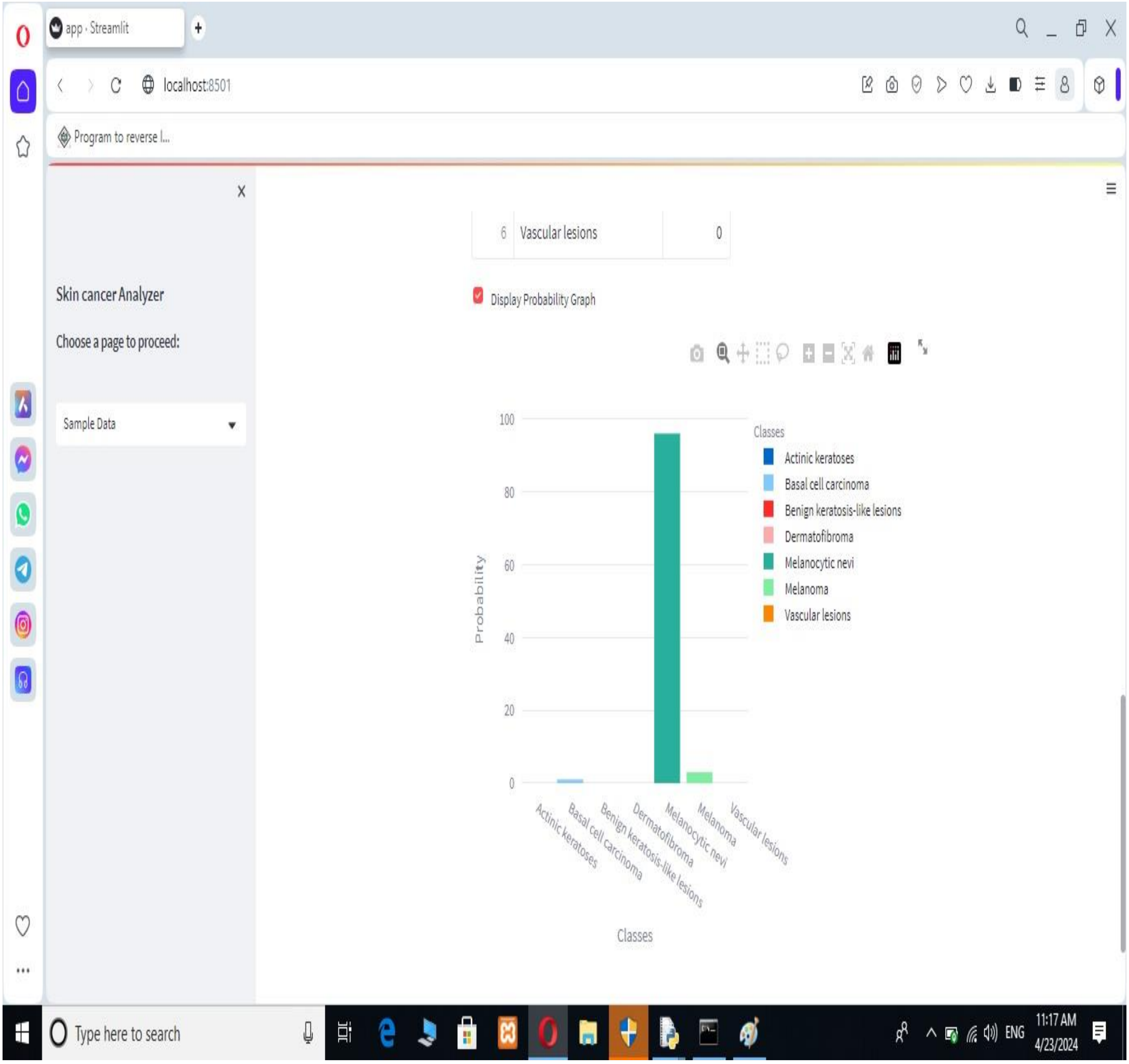

Fig A1.6 Displaying the bar chart diagram result of sample data

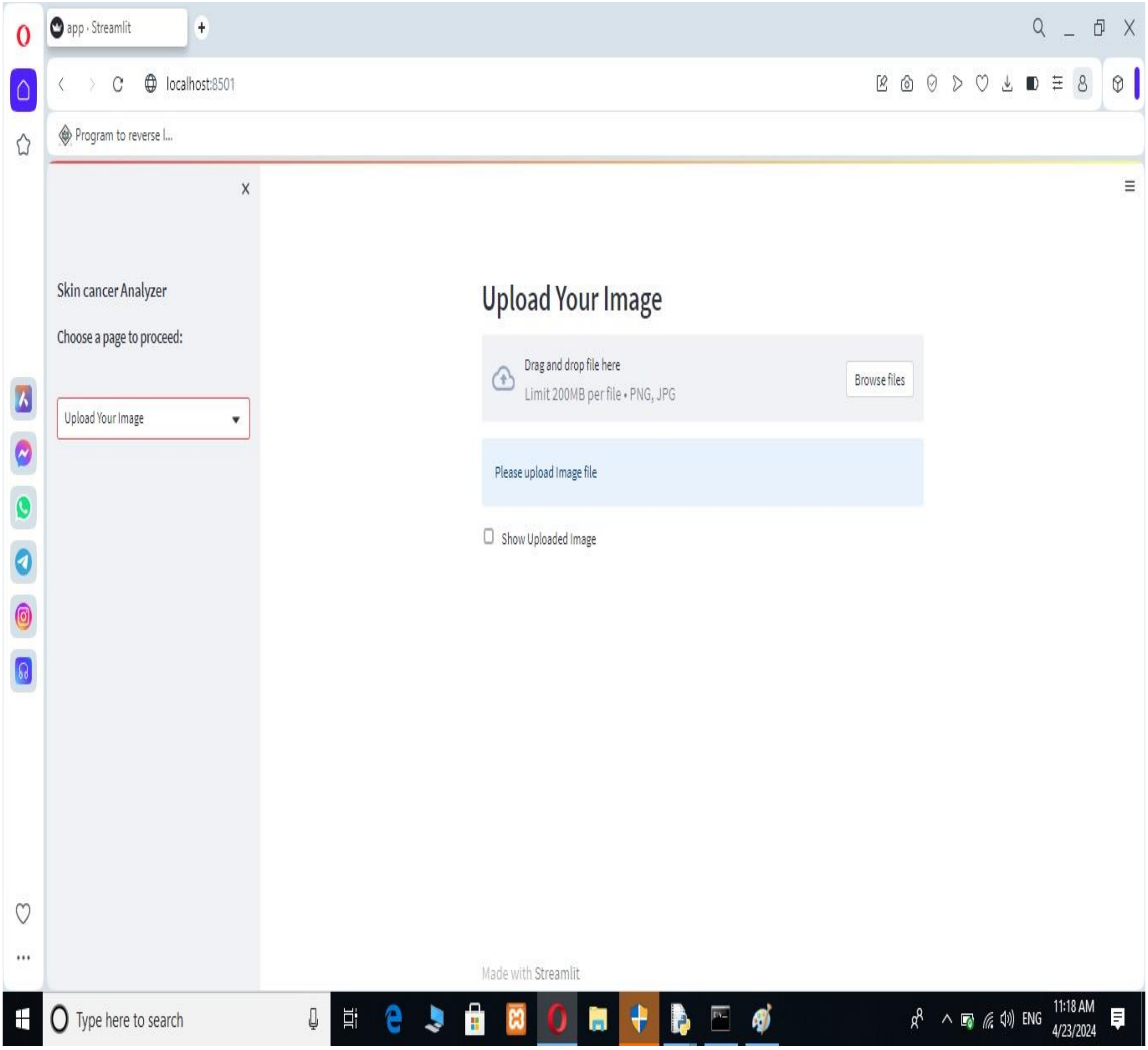

Fig A1.7 Uploading the user input image

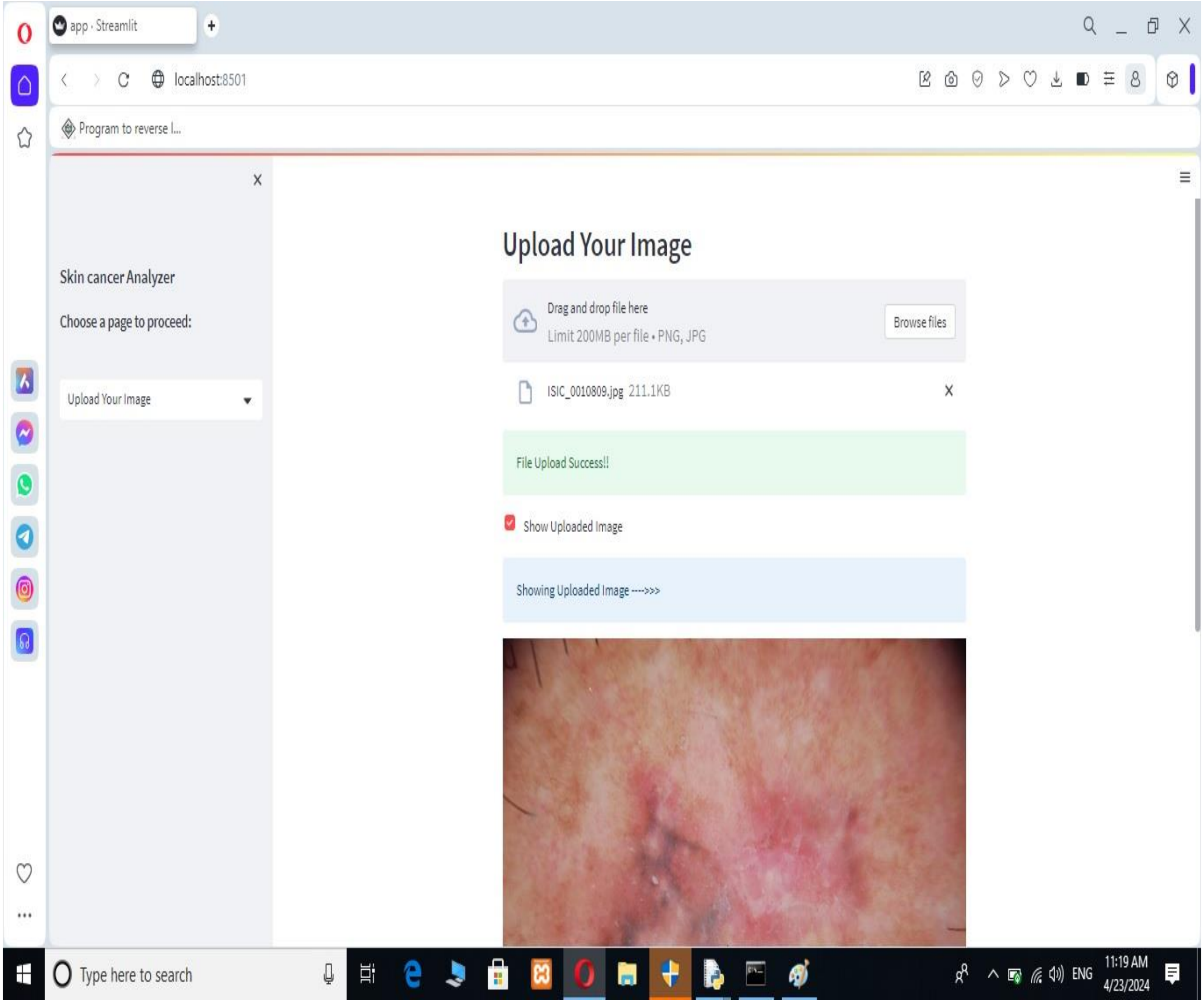

Fig A1.8 Displaying the user input image

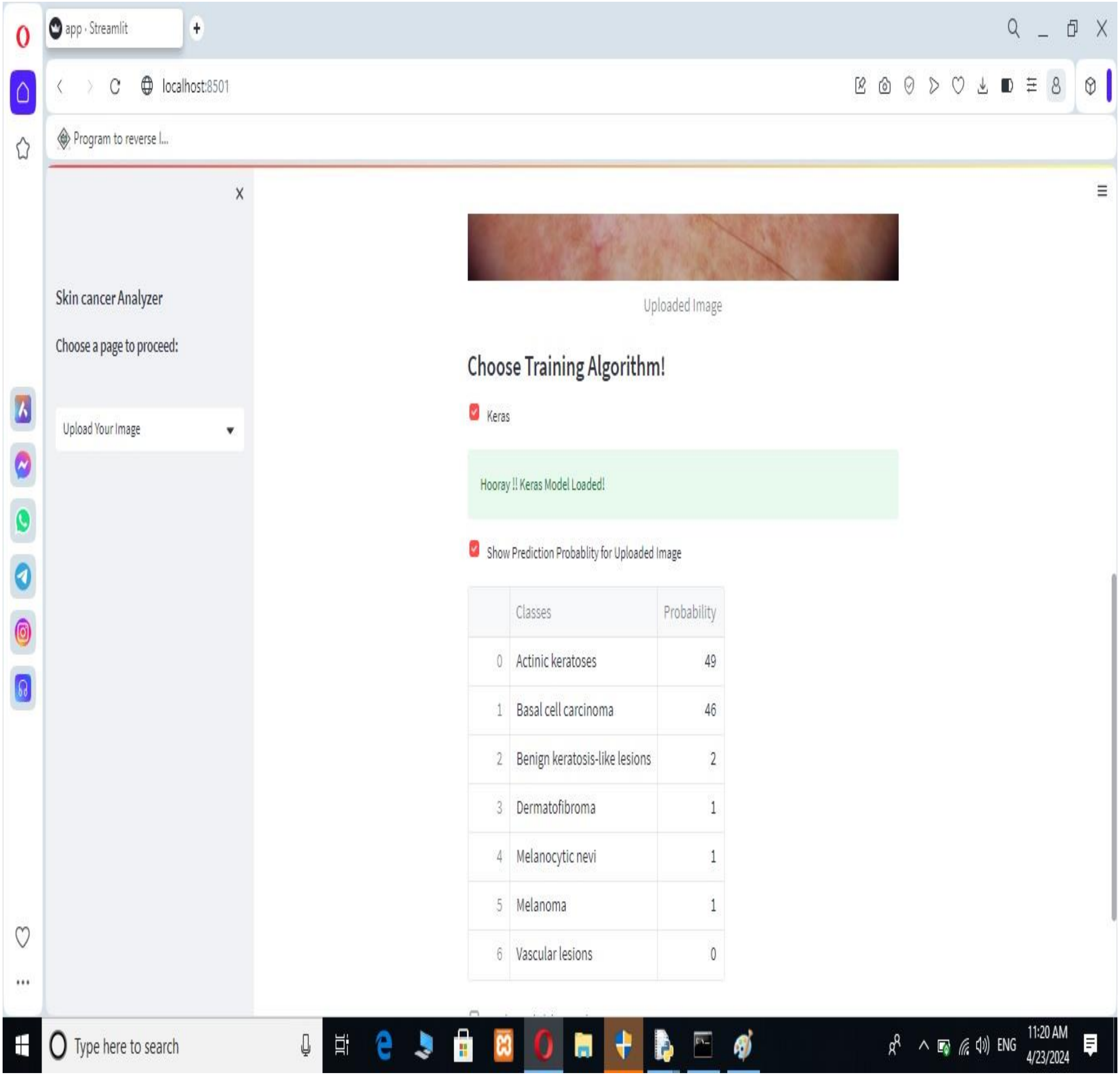

Fig A1.8 Displaying the user input image affected percentage

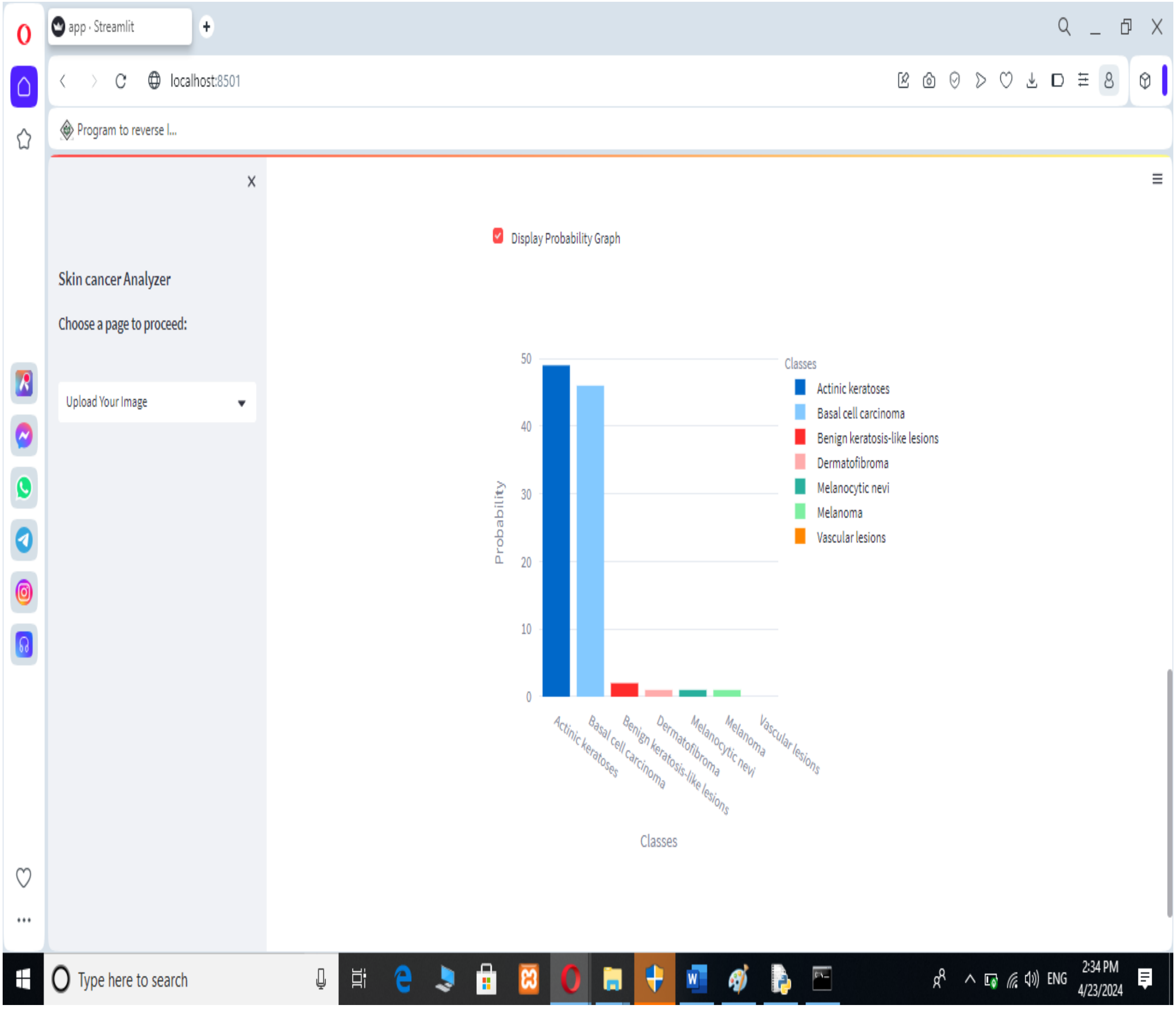

Fig A1.9 Displaying the bar chart diagram result of user input image

A.2 SAMPLE SOURCE CODE

```
import streamlit as st
import numpy as np
import pandas as pd
import keras
from keras.utils.np_utils import to_categorical
from keras.models import Sequential, load_model
from keras import backend as K
import os
import time
import io
from PIL import Image
import plotly.express as px
def loadlottie(url:str):
 r=requests.get(url)
 if r.status_code!=200:
    return None
 return r.json()

lottie_doctor=loadlottie("https://assets10.lottiefiles.com/packages/lf20_psylrdq8.json")
st_lottie(
```

```
lottie_doctor,
  speed=3,
  reverse=False,
  loop=True,
  quality="high",
  height=None,
  width=None,
  key=None,
  )
   MODELSPATH = './models/'
   DATAPATH = './data/'
   def render_header():
   st.write("""
    <p align="center">
    <H1> Skin cancer Analyzer  </H1>
    </p>
    """, unsafe_allow_html=True)
    @st.cache_data
     def load_mekd():
     img = Image.open( DATAPATH + '/ISIC_0024312.jpg')
     return img
    @st.cache_data
```

```
def data_gen(x):
    img = np.asarray(Image.open(x).resize((100, 75)))
    x_test = np.asarray(img.tolist())
    x_test_mean = np.mean(x_test)
    x_test_std = np.std(x_test)
    x_test = (x_test - x_test_mean) / x_test_std
    x_validate = x_test.reshape(1, 75, 100, 3)
    return x_validate
  @st.cache_data
  def data_gen_(img):
  img = img.reshape(100, 75)
  x_test = np.asarray(img.tolist())
  x_test_mean = np.mean(x_test)
  x_test_std = np.std(x_test)
  x_test = (x_test - x_test_mean) / x_test_std
  x_validate = x_test.reshape(1, 75, 100, 3)
  return x_validate
```

```
def load_models():
    model = load_model(MODELSPATH + 'model.h5')
    return model
def predict(x_test, model):
    Y_pred = model.predict(x_test)
    #ynew = np.argmax(Y_pred,axis=1)
    ynew = model.predict(x_test)
    K.clear_session()
    ynew = np.round(ynew, 2)
    ynew = ynew*100
    y_new = ynew[0].tolist()
    Y_pred_classes = np.argmax(Y_pred, axis=1)
    K.clear_session()
    return y_new, Y_pred_classes


  def display_prediction(y_new):
      """Display image and preditions from model"""


    result = pd.DataFrame({'Probability': y_new}, index=np.arange(7))
    result = result.reset_index()
    result.columns = ['Classes', 'Probability']
```

```
lesion_type_dict = {2: 'Benign keratosis-like lesions', 4: 'Melanocytic nevi', 3:
'Dermatofibroma',5: 'Melanoma', 6: 'Vascular lesions', 1: 'Basal cell carcinoma', 0:
'Actinic keratoses'}

 result["Classes"] = result["Classes"].map(lesion_type_dict)
 return result

 def main():
 st.sidebar.header('Skin cancer Analyzer')
 st.sidebar.subheader('Choose a page to proceed:')
 page = st.sidebar.selectbox("", ["Sample Data", "Upload Your Image"])

 if page == "Sample Data":
 st.header("Sample Data Prediction for Skin Cancer")

st.markdown("""
**Now, this is probably why you came here. Let's get you some Predictions**
You need to choose Sample Data
""")
mov_base = ['Sample Data I']
movies_chosen = st.multiselect('Choose Sample Data', mov_base)
```

```
if len(movies_chosen) > 1:
    st.error('Please select Sample Data')
if len(movies_chosen) == 1:
    st.success("You have selected Sample Data")
else:
    st.info('Please select Sample Data')


if len(movies_chosen) == 1:
    if st.checkbox('Show Sample Data'):
        st.info("Showing Sample data---->>>")
        image = load_mekd()
        st.image(image, caption='Sample Data', use_column_width=True)
        st.subheader("Choose Training Algorithm!")


         if st.checkbox('Keras'):
            model = load_models()
            st.success("Hooray !! Keras Model Loaded!")
            if st.checkbox('Show Prediction Probablity on Sample Data'):
                x_test = data_gen(DATAPATH + '/ISIC_0024312.jpg')
                y_new, Y_pred_classes = predict(x_test, model)
                result = display_prediction(y_new)
                st.write(result)
```

```
            if st.checkbox('Display Probability Graph'):
                fig = px.bar(result, x="Classes",
                 y="Probability", color='Classes')
                st.plotly_chart(fig, use_container_width=True)

 if page == "Upload Your Image":

     st.header("Upload Your Image")

     file_path = st.file_uploader('Upload an image', type=['png', 'jpg'])

     if file_path is not None:
        x_test = data_gen(file_path)
        image = Image.open(file_path)
        img_array = np.array(image)
    st.success('File Upload Success!!')
else:
    st.info('Please upload Image file')
if st.checkbox('Show Uploaded Image'):
    st.info("Showing Uploaded Image ---->>>")
    st.image(img_array, caption='Uploaded Image',
             use_column_width=True)
    st.subheader("Choose Training Algorithm!")
    if st.checkbox('Keras'):
        model = load_models()
        st.success("Hooray !! Keras Model Loaded!")
```

```
if st.checkbox('Show Prediction Probablity for Uploaded Image'):
        y_new, Y_pred_classes = predict(x_test, model)
        result = display_prediction(y_new)
        st.write(result)
        if st.checkbox('Display Probability Graph'):
          fig = px.bar(result, x="Classes",
                    y="Probability", color='Classes')
          st.plotly_chart(fig, use_container_width=True)
 no_of_classes = len(np.unique(y_train))
 y_train = np_utils.to_categorical(y_train,no_of_classes)
 y_test = np_utils.to_categorical(y_test,no_of_classes)
 y_train[0]

 x_train, x_valid, y_train, y_valid = train_test_split(x_train, y_train,
 test_size = 0.1, random_state = 2)
 x_train = x_train.reshape(x_train.shape[0], *(75, 100, 3))
 x_test = x_test.reshape(x_test.shape[0], *(75, 100, 3))
 x_valid = x_valid.reshape(x_valid.shape[0], *(75, 100, 3))
 x_train = x_train.astype('float32')/255
 x_valid = x_valid.astype('float32')/255
 x_test = x_test.astype('float32')/255
```

```
x_train[0]
fig = plt.figure(figsize =(30,5))
for i in range(10):
   ax = fig.add_subplot(2,5,i+1,xticks=[],yticks=[])
   ax.imshow(np.squeeze(x_train[i]))

def accuracy(outputs, labels):
   _, preds = torch.max(outputs, dim=1)
  return torch.tensor(torch.sum(preds == labels).item() / len(preds))

class ImageClassificationBase(nn.Module):
   def training_step(self, batch):
         images, labels = batch
         out = self(images)
         loss = F.cross_entropy(out, labels)
         return loss
    def validation_step(self, batch):
         images, labels = batch
```

```
        out = self(images)
        loss = F.cross_entropy(out, labels)
        acc = accuracy(out, labels)
        return {'val_loss': loss.detach(), 'val_acc': acc}

    def validation_epoch_end(self, outputs):
        batch_losses = [x['val_loss'] for x in outputs]
        epoch_loss = torch.stack(batch_losses).mean()   # Combine losses
        batch_accs = [x['val_acc'] for x in outputs]
        epoch_acc = torch.stack(batch_accs).mean()      # Combine accuracies
        return {'val_loss': epoch_loss.item(), 'val_acc': epoch_acc.item()}
    def epoch_end(self, epoch, result):
        print("Epoch [{}], train_loss: {:.4f}, val_loss: {:.4f}, val_acc: {:.4f}".format(
        epoch, result['train_loss'], result['val_loss'], result['val_acc']))

class SkinModel(ImageClassificationBase):
    def __init__(self):
        super().__init__()
        self.network = nn.Sequential(
```

```
        nn.Conv2d(3, 16, kernel_size=3, padding=1),

        nn.ReLU(),

        nn.MaxPool2d(2, 2),

        nn.Conv2d(16,32, kernel_size=3, stride=1, padding=1),

        nn.ReLU(),

        nn.MaxPool2d(2, 2),

        nn.Conv2d(32,64, kernel_size=3, stride=1, padding=1),

        nn.ReLU(),

        nn.MaxPool2d(2, 2),

        nn.Flatten(),

        nn.Linear(64*28*28, 500),

        nn.ReLU(),

        nn.Linear(500, 2),

        nn.Softmax())


    def forward(self, xb):

        return self.network(xb)



if(selected == 'Skin Cancer Prediction'):

    st.title("Skin Cancer Prediction")
```

```
def skin():
    os.chdir('C:/Users/ELCOT/AppData/Local/Programs/Python/
    Python39/myenv/cinimas/Skin-cancer-Analyzer-master')
     subprocess.run([f"{sys.executable}","C:/Users/ELCOT/
    AppData/Local/Programs/Python/Python39/myenv/cinimas/Skin-cancer-
    Analyzer-master/app.py"])
    msg6='streamlit run
    C:/Users/ELCOT C:/Users/ELCOT/AppData/Local/Programs/Python
    /Python39/myenv/cinimas/Skin-cancer-Analyzer-master/app.py'
     p=subprocess.Popen(msg6, stdout=subprocess.PIPE, shell=True)
     out,err=p.communicate()
     result=out.split('\n')
for lin in result:
    if not lin.startswith('#'):
        print(lin)


def run_skin():
    st.button("Skin Cancer Prediction",on_click=skin)
    run_skin()
if __name__ == "__main__":
        main()
```

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