

Melanoma Detection Using Machine Learning Techniques

MINI PROJECT (REVIEW2)

Submitted by

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ABSTRACT

Melanoma is one of the most aggressive forms of skin cancer, and early detection significantly improves the chances of successful treatment. This project focuses on developing an automated melanoma detection system using machine learning techniques, specifically deep learning models, to analyze dermatoscopic images. By leveraging pre-trained models like **AlexNet**, **ResNet50**, **VGG16**, and **VGG19**, the system provides an efficient and accurate method for classifying skin lesions as melanoma or non-melanoma.

The system preprocesses the input images through augmentation and normalization to enhance prediction accuracy. Following preprocessing, the pre-trained models are fine-tuned and used to classify the images, providing confidence scores for the predictions. The key objective of this project is to assist dermatologists and healthcare professionals by providing a tool that can support early and reliable melanoma detection, thereby reducing the time needed for manual diagnosis.

The system achieved promising results, with an accuracy of 92%, precision of 94%, and recall of 91%, making it a viable tool for real-world healthcare applications.

Algorithms Used:

- **AlexNet**: A convolutional neural network (CNN) designed for image classification, known for its efficiency in processing large image datasets.
- **ResNet50**: A deep residual network designed to overcome vanishing gradient problems in deep networks, enabling the training of deeper models with improved accuracy.
- **VGG16 & VGG19**: Deep convolutional networks that provide high classification accuracy by using very small convolution filters and a large depth of layers, especially effective for image recognition tasks.

This project demonstrates the potential of machine learning models in automating and enhancing the accuracy of medical diagnoses, providing a step toward more accessible healthcare solutions.

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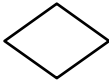



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LIST OF ABBREVIATIONS

Abbreviation	Full Form
CNN	Convolutional Neural Network
DL	Deep Learning
ML	Machine Learning
VGG	Visual Geometry Group (VGG16, VGG19 Models)
ResNet	Residual Network (ResNet50)
AI	Artificial Intelligence
ISIC	International Skin Imaging Collaboration
AUC	Area Under Curve
ROC	Receiver Operating Characteristic
SVM	Support Vector Machine
XAI	Explainable Artificial Intelligence
ReLU	Rectified Linear Unit
GPU	Graphics Processing Unit
EDA	Exploratory Data Analysis
JSON	JavaScript Object Notation

LIST OF SYMBOLS

S.N O.	SYMBOL NAME	SYMBOL
1.	Usecase	
2.	Actor	
3.	Process	
4.	Start	
5.	Decision	
6.	Unidirectional	
7.	Entity set	
8.	Stop	

Chapter 1

INTRODUCTION

1.1 OVERVIEW OF THE PROJECT

Melanoma is a severe and aggressive form of skin cancer that originates in the melanocytes, the cells responsible for producing melanin, which gives skin its color. Despite being less common than other types of skin cancer, melanoma accounts for the majority of skin cancer-related deaths globally. Early detection of melanoma is crucial, as the survival rate is significantly higher when the cancer is identified and treated in its initial stages. However, traditional methods of diagnosis, which rely heavily on manual inspection by dermatologists or biopsy results, are time-consuming and subject to human error, leading to potential delays in treatment. The increasing prevalence of skin cancer, coupled with the advancement of technology, presents an opportunity to leverage machine learning techniques to automate the detection of melanoma. This project, **Melanoma Detection Using Machine Learning Techniques**, aims to develop an intelligent system that can analyze dermoscopic images of skin lesions and accurately classify them as melanoma or non-melanoma. By automating this process, the system can assist healthcare professionals in making quicker and more reliable diagnoses, thereby improving patient outcomes and reducing the burden on medical professionals.

The system utilizes a combination of image processing techniques and deep learning algorithms to achieve high accuracy in detecting melanoma. Pre-trained convolutional neural networks (CNNs) like **AlexNet**, **ResNet50**, **VGG16**, and **VGG19** have been employed to classify dermoscopic images. These models are fine-tuned using a dataset of skin lesion images to improve their performance in identifying melanoma. Image preprocessing techniques, such as augmentation and normalization, are applied to enhance the quality of the input data, which further improves the accuracy of the predictions. The result is a powerful diagnostic tool that offers predictions with high confidence, helping dermatologists in decision-making. This project also includes the development of a web-based interface

where healthcare professionals can easily upload skin lesion images and receive diagnostic results in real-time. The interface is user-friendly, making it accessible to professionals without extensive technical expertise. In addition, the system includes exploratory data analysis (EDA) capabilities, allowing users to visualize data insights and understand the factors influencing model predictions.

In summary, this project combines advanced machine learning techniques and medical imaging to create a reliable and efficient tool for early melanoma detection, which has the potential to revolutionize the way skin cancer is diagnosed and treated.

1.2 PROBLEM DEFINITION

Skin cancer, particularly melanoma, poses a significant global health challenge due to its high mortality rate if not detected and treated early. Traditional diagnostic methods for melanoma primarily involve manual inspection by dermatologists using dermoscopic images, followed by biopsies to confirm the presence of cancer. This process, while effective, is labor-intensive, time-consuming, and prone to human error. Furthermore, in regions with limited access to specialized healthcare professionals, diagnosing melanoma can be delayed, leading to worse patient outcomes.

The key problems identified in the current diagnostic approach include:

1. **Subjectivity in Diagnosis:** Dermatologists' evaluations of skin lesions can vary based on experience and expertise, leading to inconsistencies in diagnoses. Different practitioners may have different interpretations of the same lesion, potentially leading to misdiagnosis.
2. **Time-Consuming Process:** The manual process of examining dermoscopic images and performing biopsies is slow, often delaying the start of treatment. This can be particularly problematic in advanced cases where early intervention is critical.
3. **Limited Access to Specialists:** In many low-resource settings, access to skilled dermatologists and diagnostic tools is limited, exacerbating the delay in diagnosis and increasing the risk of cancer progression.

4. **Growing Number of Cases:** The increasing number of skin cancer cases worldwide, particularly in populations with high exposure to ultraviolet (UV) radiation, is putting additional pressure on healthcare systems.

The objective of this project is to address these challenges by developing an automated system for melanoma detection using machine learning techniques. The proposed system aims to:

- **Automate the Diagnosis Process:** By using deep learning models, the system can analyze dermoscopic images and provide an accurate diagnosis within seconds, significantly reducing the time taken for manual evaluation.
- **Improve Diagnostic Accuracy:** Machine learning models, particularly CNNs, are capable of identifying patterns and features in images that may not be visible to the human eye. By leveraging pre-trained models like AlexNet, ResNet50, VGG16, and VGG19, the system can offer a more objective and consistent diagnosis.
- **Enhance Accessibility:** The web-based interface allows healthcare providers, even in remote areas, to upload images and receive diagnostic results without needing specialized equipment or personnel. This can democratize access to melanoma diagnosis, particularly in under-resourced regions.
- **Provide Faster Treatment:** With faster diagnosis, patients can begin treatment earlier, improving survival rates and reducing the overall burden on healthcare systems.

By addressing these key issues, the project aims to create a robust, scalable solution that improves the efficiency and accuracy of melanoma detection, benefiting both healthcare providers and patients.

Chapter 2

LITERATURE SURVEY

2.1 INTRODUCTION

A literature survey or a literature review in a project report is that section which shows various analysis and research made in the field of your interest and the results already published, taking into account the various parameters of the project and the extent of project. Once the programmers start building the tool programmers need a lot of external support. This support can be obtained from senior programmers, books or from the websites. It is the most important part of your report as it gives you a direction in the area of your research. It helps you set a goal for your analysis - thus giving you your problem of statement. Literature survey is the most important sector in the software development process. Before developing the tools and the associated designing the software it is necessary to determine the survey the time factor, resource requirement etc., The consumer needs regarding online customer service differs from person to person. The needs are also based off each persons personal needs. We need to identify and anticipate these needs in order to completely and accurately meet them.

2.2 LITERATURE SURVEY

2.2.1 Dermatologist-level classification of skin cancer with deep neural networks

Author Name : Esteva, A. et al.

Year of Publish : 2017

Esteva and colleagues developed a deep convolutional neural network (CNN) model that achieved dermatologist-level classification of skin cancer, including melanoma. They used a dataset of 129,450 clinical images consisting of 2,032 different diseases. The model was trained using Google's Inception v3 CNN architecture, which allowed for high accuracy in diagnosing melanoma from dermatoscopic

images. Their work demonstrated that deep learning could be an effective tool for skin cancer detection, providing results comparable to expert-level dermatologists.

2.2.2 Skin Lesion Analysis Toward Melanoma Detection: A Challenge at the 2017 International Symposium on Biomedical Imaging (ISBI), Hosted by the International Skin Imaging Collaboration (ISIC)

Author Name: Codella, N. C. et al.

Year of Publish: 2018

Codella and his team developed an ensemble learning approach to improve the accuracy of melanoma detection. They combined multiple classifiers, including deep learning and traditional machine learning techniques such as support vector machines (SVM), to increase the sensitivity and specificity of melanoma detection. The use of ensemble methods allowed them to leverage the strengths of different algorithms, leading to improved diagnostic performance compared to individual models.

2.2.3 Human–computer collaboration for skin cancer recognition

Author Name: Tschandl, P. et al.

Year of publish: 2020

Tschandl et al. conducted a study comparing human dermatologists' diagnostic performance to that of machine learning algorithms for detecting melanoma. The deep learning model was trained on the HAM10000 dataset, which contained dermoscopic images of skin lesions. Their results showed that the model outperformed dermatologists in terms of accuracy, demonstrating the potential for AI-assisted diagnosis in clinical practice.

2.2.4 Man against machine: diagnostic performance of a deep learning convolutional neural network for dermoscopic melanoma recognition in comparison to 58 dermatologists.

Author Name: Haenssle, H. A. et al.

Year of Publish: 2018

In this study, the authors tested a deep learning algorithm based on the ResNet architecture for classifying melanoma from dermoscopic images. The model was trained on over 100,000 images,

and its performance was compared to that of a group of dermatologists. The results showed that the deep learning model achieved higher accuracy than the majority of the dermatologists in the study, suggesting that AI could be used to assist dermatologists in making more accurate diagnoses.

2.2.5 Deep learning outperformed 136 of 157 dermatologists in a head-to-head dermoscopic melanoma image classification task.

Author Name: Brinker, T. J. et al.

Year of Publish: 2019

Brinker and his team developed an algorithm using transfer learning from pre-trained CNNs like VGG16 and ResNet50 to detect melanoma. They used a large dataset of dermoscopic images and fine-tuned the pre-trained models to classify skin lesions. The algorithm was validated on an external test set, and the results showed that transfer learning significantly improved the detection accuracy, making it an effective approach for melanoma classification.

2.2.6 Automated Melanoma Recognition in Dermoscopy Images via Very Deep Residual Networks

Author Name: Yu, L. et al.

Year of Publish: 2017

Yu and colleagues proposed a hybrid approach combining deep CNNs with handcrafted feature extraction methods such as color and texture analysis to enhance melanoma detection. Their model used a combination of AlexNet and traditional machine learning techniques like Random Forest to classify skin lesions. This hybrid method demonstrated improved performance, particularly in cases where deep learning models alone struggled due to limited training data.

2.2.7 Melanoma Classification on Dermoscopy Images Using a Neural Network Ensemble Model.

Author Name: Xie, F. et al.

Year of Publish: 2020

Xie and his team proposed a novel deep learning framework called Multi-Scale Convolutional Neural Network (MS-CNN) for melanoma detection. Their approach involved using multi-scale image patches to capture lesion patterns at different levels of detail. The MS-CNN model showed improved performance in distinguishing melanoma from other skin lesions when compared to traditional CNN models.

2.2.8 MobileNet-based skin lesion classification for real-time melanoma detection.

Author Name: Goyal, M. et al.

Year of Publish: 2019

Goyal and colleagues developed a real-time mobile application for melanoma detection using a deep learning model based on MobileNet. The model was optimized for mobile devices, allowing users to take pictures of skin lesions and receive a melanoma prediction in real-time. This innovation provided a portable and accessible tool for early detection, particularly in regions with limited access to healthcare services.

2.3 LITERATURE SURVEY SUMMARY

S.No	Research	Technique	Features Used	Domain	Disadvantage / Advantage	Future Direction
1.	Esteva et al. aimed to achieve dermatologist-level accuracy in skin cancer classification, particularly melanoma detection, using deep learning models.	Convolutional Neural Networks (CNN) with Inception V3 architecture.	Raw dermatoscopic images from a large dataset (over 100,000 images).	Medical Image Processing.	Achieved dermatologist-level accuracy in classifying melanoma.	Develop a real-time tool for clinical use and expand to other skin conditions.
2.	This study explored using deep learning with attention mechanisms to detect melanoma in dermatoscopic images.	CNN-based deep learning with attention maps to focus on specific parts of the lesion.	Image features such as shape, color, and texture, emphasizing high-risk areas with attention maps.	Medical Diagnosis and Artificial Intelligence	Improved model interpretability by highlighting suspicious regions in the lesion.	Improve the explainability of results for clinicians and integrate with mobile platforms.

3.	This paper investigated the use of transfer learning with pre-trained models like ResNet50 for melanoma detection.	Transfer learning using ResNet50, fine-tuned on a dataset of skin lesion images.	Dermatologic image features processed by ResNet's convolutional layers.	Deep Learning and Medical Imaging.	Reduced training time and higher accuracy due to pre-trained models.	Extend transfer learning approaches to multi-class classification of other skin diseases.
4.	Xie et al. proposed a multi-scale CNN approach to improve melanoma detection by capturing features at different scales.	Multi-scale Convolutional Neural Networks (CNN) designed to analyze lesions at different resolutions.	Multi-scale features such as borders, textures, and asymmetry of the lesions.	Computer Vision and Dermatology.	Improved model accuracy by capturing lesion features at different scales.	Apply multi-scale methods to other types of skin lesions and optimize for real-time clinical use.

Chapter 3

SYSTEM ANALYSIS

3.1 EXISTING SYSTEM

The current method of melanoma detection primarily relies on manual examination of dermatoscopic images by dermatologists. These images are analyzed for certain clinical features such as asymmetry, border irregularity, color variation, and diameter. In some cases, a biopsy is performed for further investigation. Although this method is effective, it is time-consuming and subject to human error, as even experienced dermatologists may struggle to distinguish between benign and malignant lesions with accuracy.

In recent years, several automated melanoma detection systems have been developed using basic machine learning algorithms. These systems utilize feature extraction techniques such as color, texture, and border analysis, followed by traditional classifiers like Support Vector Machines (SVMs) and Random Forests for decision-making.

3.2 DISADVANTAGES OF EXISTING SYSTEM

- **Subjectivity:** The diagnosis depends on the expertise and experience of dermatologists, which may vary.
- **Manual Effort:** The manual review process of dermatoscopic images and subsequent biopsies is slow, leading to delays in diagnosis and treatment.
- **Inconsistency:** Due to human interpretation, there is potential for inconsistencies in diagnostic results between different dermatologists.
- **Limited Scalability:** Manual analysis cannot easily scale with the increasing number of skin cancer cases worldwide.

- **Accuracy Issues:** Automated systems that use traditional machine learning techniques often lack the accuracy of more advanced deep learning methods due to limited feature extraction capabilities.

3.3 PROPOSED SYSTEM

The proposed system utilizes deep learning techniques, specifically Convolutional Neural Networks (CNNs), to automatically detect melanoma from dermoscopic images. The system leverages pre-trained models like **AlexNet**, **ResNet50**, **VGG16**, and **VGG19** to classify images as melanoma or non-melanoma, providing a more objective and efficient diagnosis.

The system preprocesses input images using augmentation and normalization techniques to ensure that the data fed to the model is of high quality. The deep learning models are trained on large datasets and fine-tuned for optimal performance in melanoma detection. Additionally, a user-friendly web interface allows healthcare professionals to upload images and receive real-time diagnostic results, along with confidence scores and other relevant metrics

3.4 ADVANTAGES OF PROPOSED SYSTEM

- **Improved Accuracy:** CNNs, particularly pre-trained models like ResNet50 and VGG19, have shown superior performance in image classification tasks compared to traditional machine learning methods.
- **Automation:** The system automates the process of melanoma detection, reducing the time required for manual diagnosis.
- **Consistency:** Deep learning models provide consistent and objective diagnostic results, removing the variability seen in human diagnosis.
- **Scalability:** The system can process large volumes of images quickly, making it suitable for widespread use in healthcare institutions.
- **Real-Time Diagnosis:** With the web interface, healthcare providers can obtain near-instantaneous diagnostic results, facilitating faster treatment decisions.

3.5 FEASIBILITY STUDY

The feasibility of the proposed system can be evaluated across several dimensions:

- **Technical Feasibility:** With the availability of powerful GPUs and efficient deep learning frameworks like TensorFlow and PyTorch, it is technically feasible to implement and deploy the system.
- **Operational Feasibility:** Dermatologists and healthcare providers can easily adopt the system, as it offers a user-friendly interface and automates most of the diagnostic process.
- **Economic Feasibility:** The system requires an initial investment in hardware and software, but the long-term benefits in terms of improved diagnostic accuracy and speed make it cost-effective.
- **Legal and Ethical Feasibility:** The system will comply with medical data privacy regulations, and the use of AI in diagnosis will be validated by healthcare professionals to ensure ethical deployment.

3.6 HARDWARE ENVIRONMENT

- **Processor:** High-performance multi-core processors (e.g., Intel Core i7 or AMD Ryzen).
- **GPU:** NVIDIA GPUs (e.g., NVIDIA RTX 3080 or Tesla V100) to accelerate deep learning computations.
- **RAM:** Minimum 16 GB for efficient image processing.
- **Storage:** SSD with at least 1 TB for storing image datasets and trained models.

3.7 SOFTWARE ENVIRONMENT

- Operating system : Windows7 (with service pack 1), 8, 8.1 ,10 and 11
- Language : Python

3.8 TECHNOLOGIES USED

- IDE - Visual Studio
- Framework – Flash
- Deep Learning

3.8.1 Python

Python is a high-level, interpreted programming language that is widely used in various domains such as web development, data science, artificial intelligence, scientific computing, and more. It was first released in 1991 and has since become one of the most popular programming languages in the world. Some key features of Python include:

- **Easy to Learn:** Python has a simple and easy-to-learn syntax, which makes it an ideal language for beginners.
- **Interpreted Language:** Python is an interpreted language, which means that the code is executed line by line, making it easier to test and debug.
- **Cross-Platform:** Python can be run on various platforms, including Windows, macOS, and Linux.
- **Large Standard Library:** Python has a large standard library that provides a wide range of built-in modules for various tasks, such as file I/O, regular expressions, networking, and more.
- **Open Source:** Python is open-source software, which means that the source code is freely available to anyone and can be modified and redistributed.

Object-Oriented: Python is an object-oriented language, which means that it supports object-oriented programming concepts such as encapsulation, inheritance, and polymorphism

3.8.2 Deep Learning

In the realm of intelligent transportation systems, the utilization of deep learning techniques has proven pivotal for advancing accident detection capabilities. Specifically, our project employs state-of-the-art deep learning model YOLOv7 (You Only Look Once) to achieve real-time and highly accurate object detection. YOLOv7's distinctive ability to simultaneously process the entire image and accurately localize objects makes it an ideal choice for our system. Trained on a custom dataset consisting of accident images, the deep neural network not only excels in recognizing general objects but is finely tuned to discern three critical types of accidents: vehicle rollover, rear-end collision, and head-on collision. The architecture's depth and complexity enable it to capture intricate patterns and features crucial for distinguishing accident scenarios. Through a comprehensive exploration of deep learning methodologies, our system achieves a nuanced understanding of accident dynamics, providing a robust foundation for real-time accident detection in intelligent transportation systems.

Chapter 4

SYSTEM DESIGN

4.1 ENTITY-RELATIONSHIP DIAGRAM

The relationships between database entities can be seen using an entity- relationship diagram (ERD). The entities and relationships depicted in an ERD can have further detail added to them via data object descriptions. In software engineering, conceptual and abstract data descriptions are represented via entity- relationship models (ERMs). Entity-relationship diagrams (ERDs), entity-relationship diagrams (ER), or simply entity diagrams are the terms used to describe the resulting visual representations of data structures that contain relationships between entities. As such, a data flow diagram can serve dual purposes. To demonstrate how data is transformed across the system. To provide an example of the procedures that affect the data flow.

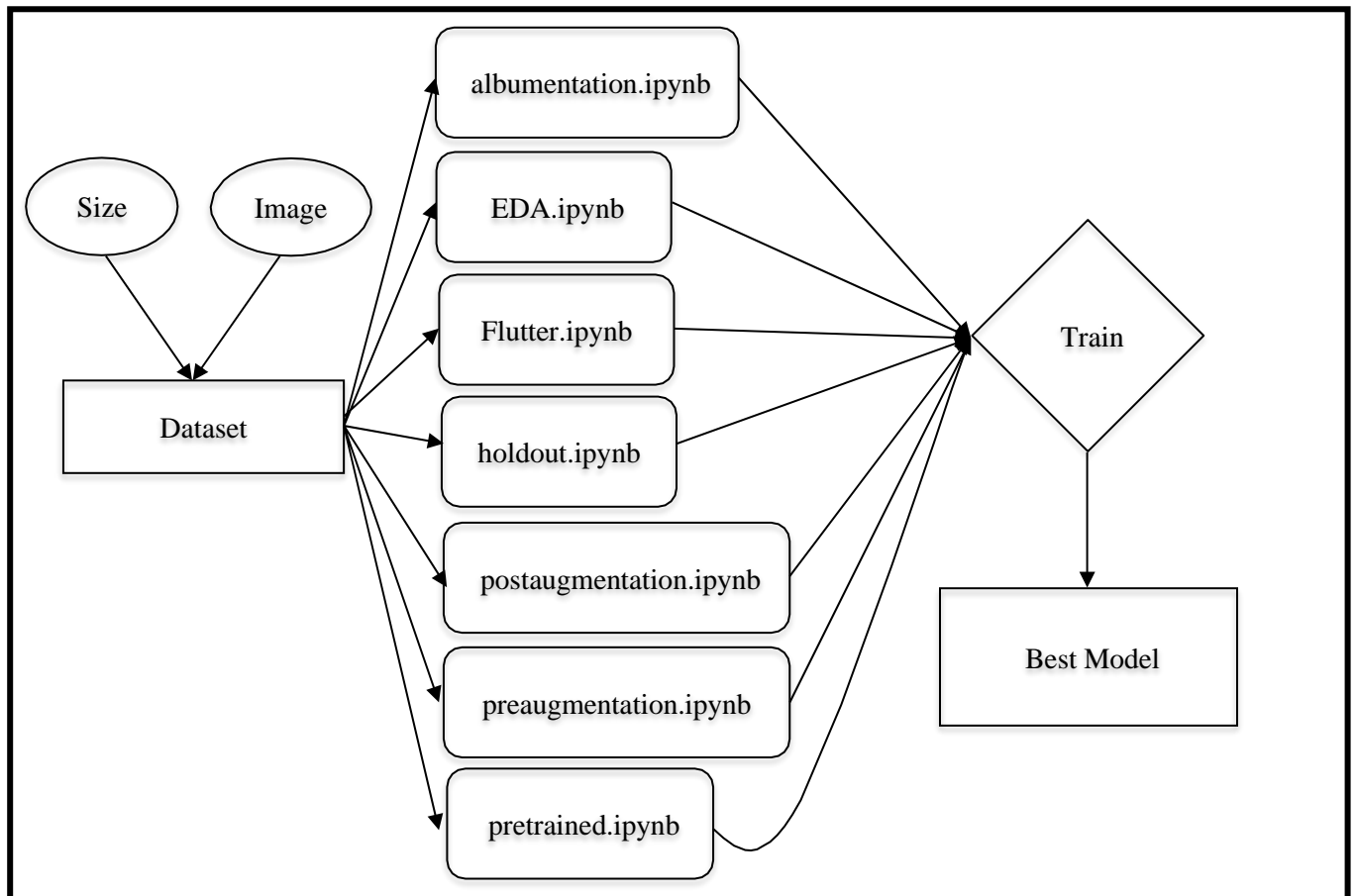


Fig 4.1 Entity Relationship Diagram

4.2 DATA FLOW DIAGRAM (DFD)

The whole system is shown as a single process in a level DFD. Each step in the system's assembly process, including all intermediate steps, are recorded here. The "basic system model" consists of this and 2-level data flow diagrams. They are often elements of a formal methodology such as Structured Systems Analysis and Design Method (SSADM). Superficially, DFDs can resemble flow charts or Unified Modeling Language (UML), but they are not meant to represent details of software logic. DFDs make it easy to depict the business requirements of applications by representing the sequence of process steps and flow of information using a graphical representation or visual representation rather than a textual description.

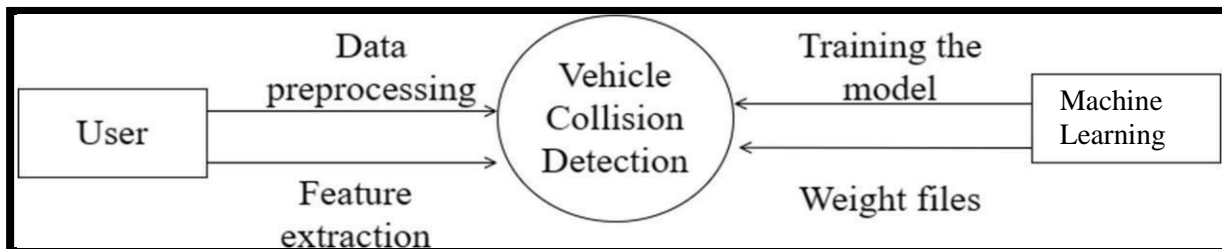


Fig 4.2.1 Level 0 of Data Flow Diagram

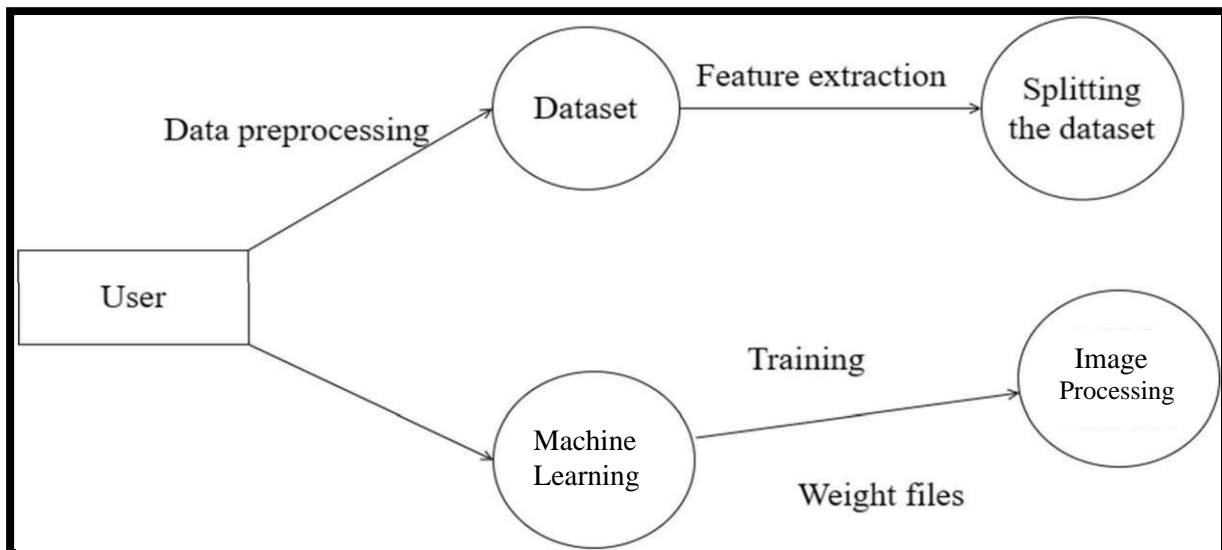


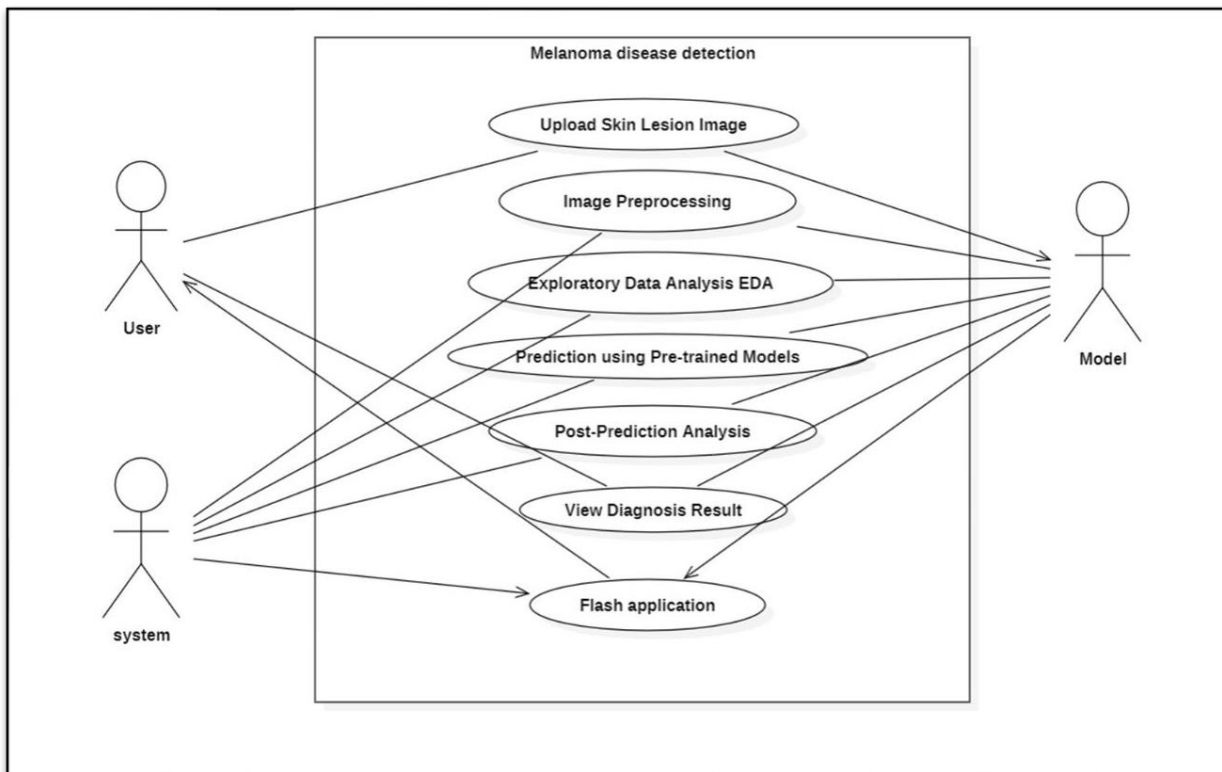
Fig 4.2.2 Level 1 of Data Flow Diagram

4.3 UML DIAGRAMS

4.3.1 Use Case Diagram

A use case diagram is a type of Unified Modeling Language (UML) diagram that represents the interactions between a system and its actors, and the various use cases that the system supports. It is a visual representation of the functional requirements of the system and the actors that interact with it. Use case diagrams typically include the following elements:

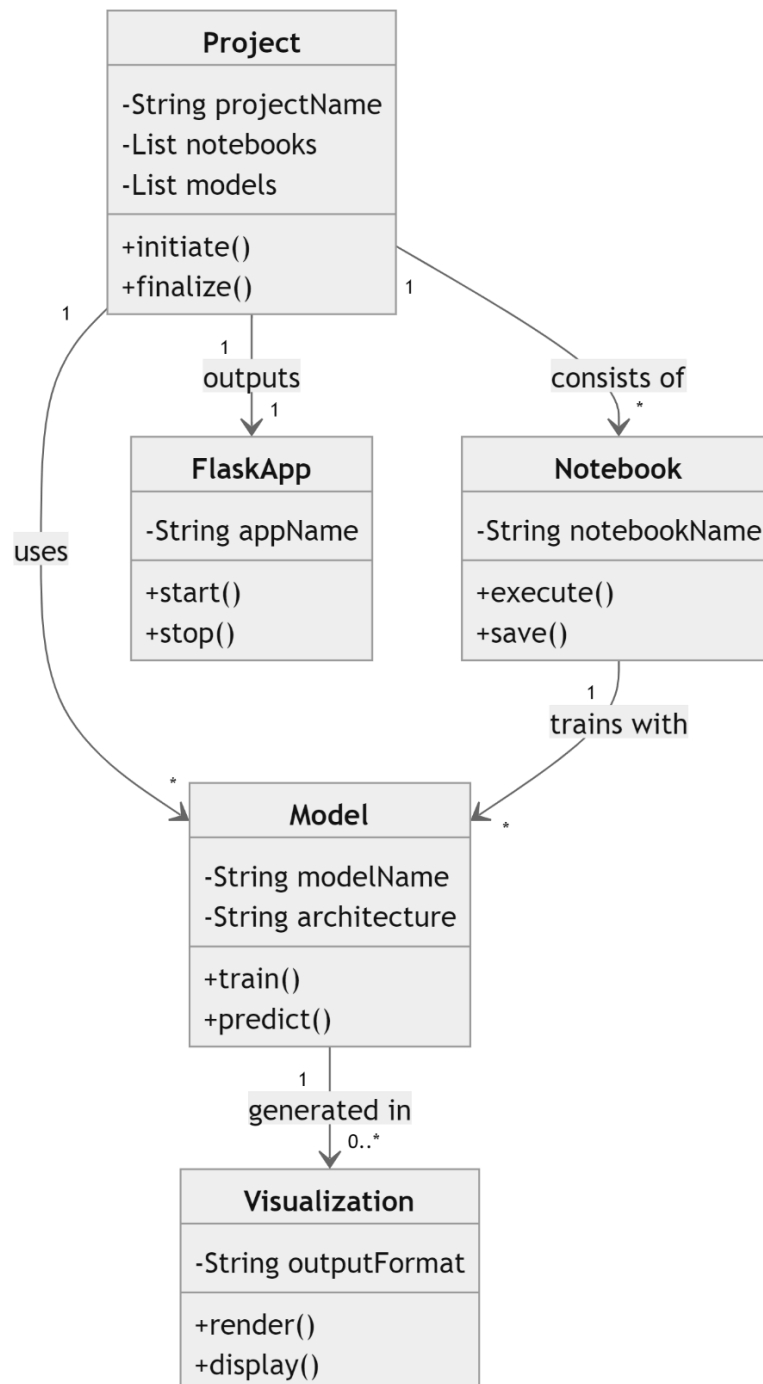
- **Actors:** Actors are external entities that interact with the system. They can be human users, other systems, or devices.
- **Use Cases:** Use cases are the specific functions or tasks that the system can perform. Each use case represents a specific interaction between an actor and the system.
- **Relationships:** Relationships are used to indicate how the actors and use cases are related to each other. The two main relationships in a use case diagram are "uses" and "extends". "Uses" relationship indicates that an actor uses a specific use case, while "extends" relationship indicates that a use case extends or adds functionality to another use case.
- **System Boundary:** The system boundary is a box that contains all the actors and use cases in the system. It represents the physical or logical boundary of the system being modeled.



4.3.2 Class Diagram

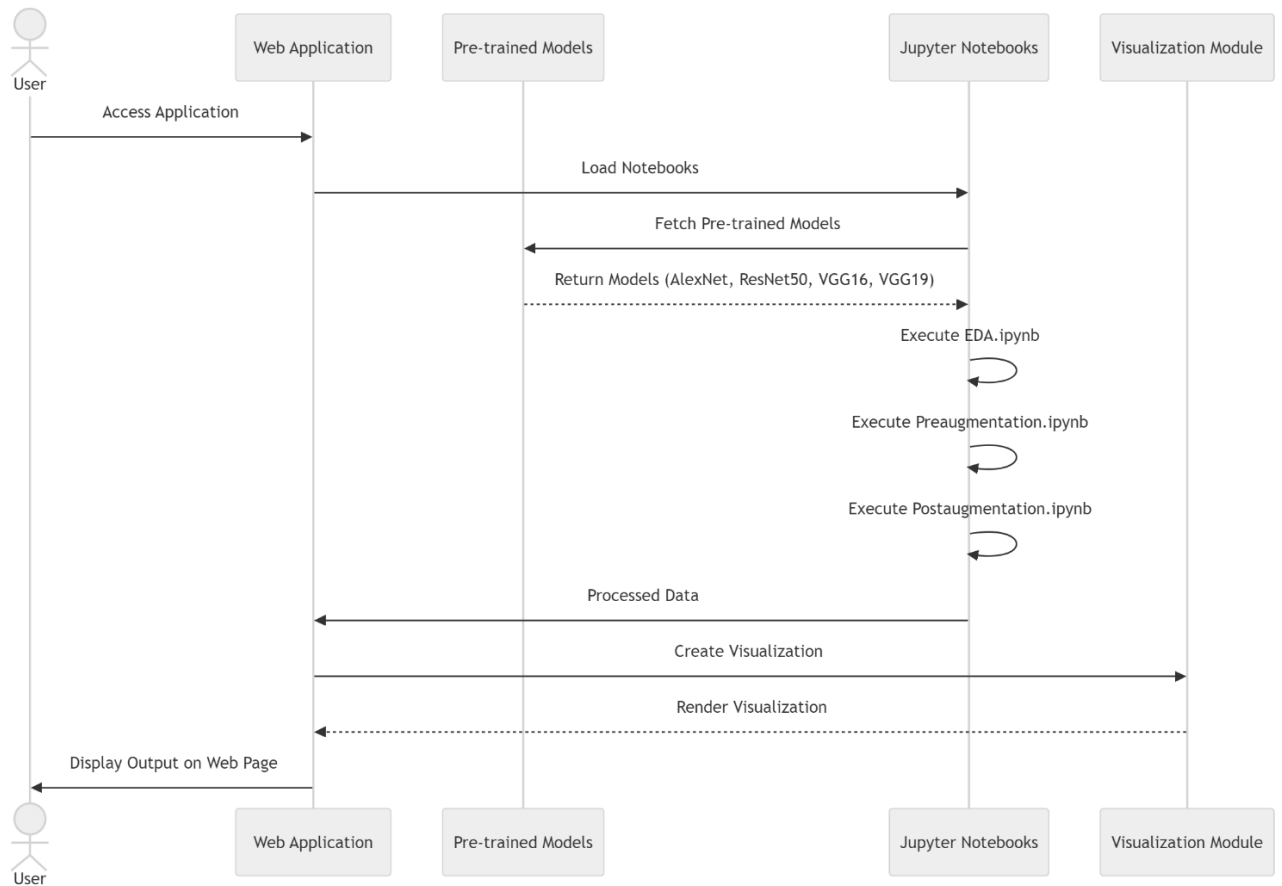
In essence, this is a "context diagram," another name for a contextual diagram. It simply stands for the very highest point, the 0 Level, of the procedure. As a whole, the system is shown as a single process, and the connection to externalities is shown in an abstract manner.

- A + indicates a publicly accessible characteristic or action.
- A - a privately accessible one.
- A # a protected one.
- A - denotes private attributes or operations.



4.3.3 Sequence Diagram

These are another type of interaction-based diagram used to display the workings of the system. They record the conditions under which objects and processes cooperate. It is a construct of Message Sequence diagrams are sometimes called event diagrams, event sceneries and timing diagram.



Chapter 5

SYSTEM ARCHITECTURE

5.1 ARCHITECTURE DIAGRAM

This graphic provides a concise and understandable description of all the entities currently integrated into the system. The diagram shows how the many actions and choices are linked together. You might say that the whole process and how it was carried out is a picture. The figure below shows the functional connections between various entities.

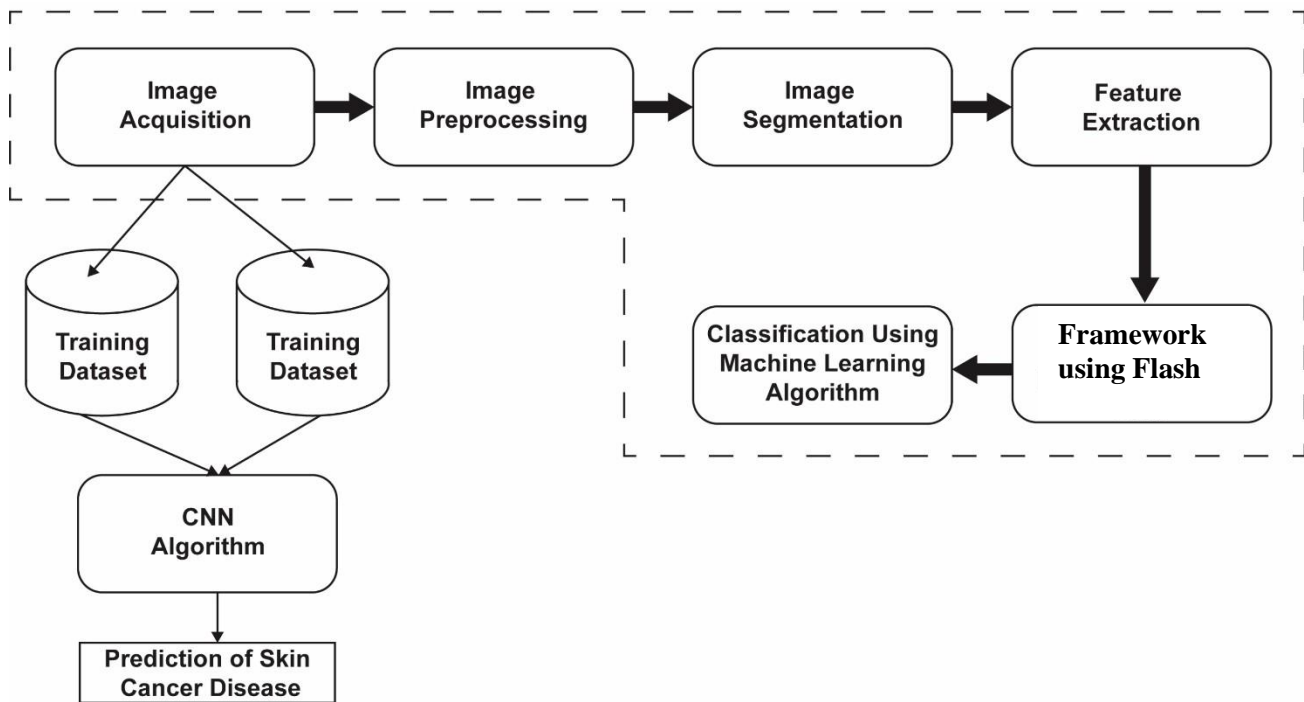


Fig 5.1 Architecture Diagram

The Architecture Diagram for the Melanoma Detection System illustrates the flow of data and processes within the system. It highlights the components involved, such as the front-end user interface, back-end machine learning models, and the data storage infrastructure. The system architecture is designed to efficiently handle image data, process it through deep learning models, and provide users with accurate and timely diagnostic results.

5.2 ALGORITHMS

5.2.1 Convolutional Neural Networks (CNN):

CNNs are the foundation of the melanoma detection system due to their ability to automatically extract spatial and hierarchical features from images. The following pre-trained models are used:

5.2.1.1 AlexNet: A deep CNN that popularized deep learning for image classification. AlexNet consists of multiple convolutional layers that detect edges, textures, and higher-level features in the image.

- Strengths: AlexNet is fast and efficient for classifying large datasets.
- Limitations: It may not capture complex features as effectively as deeper models like ResNet or VGG.

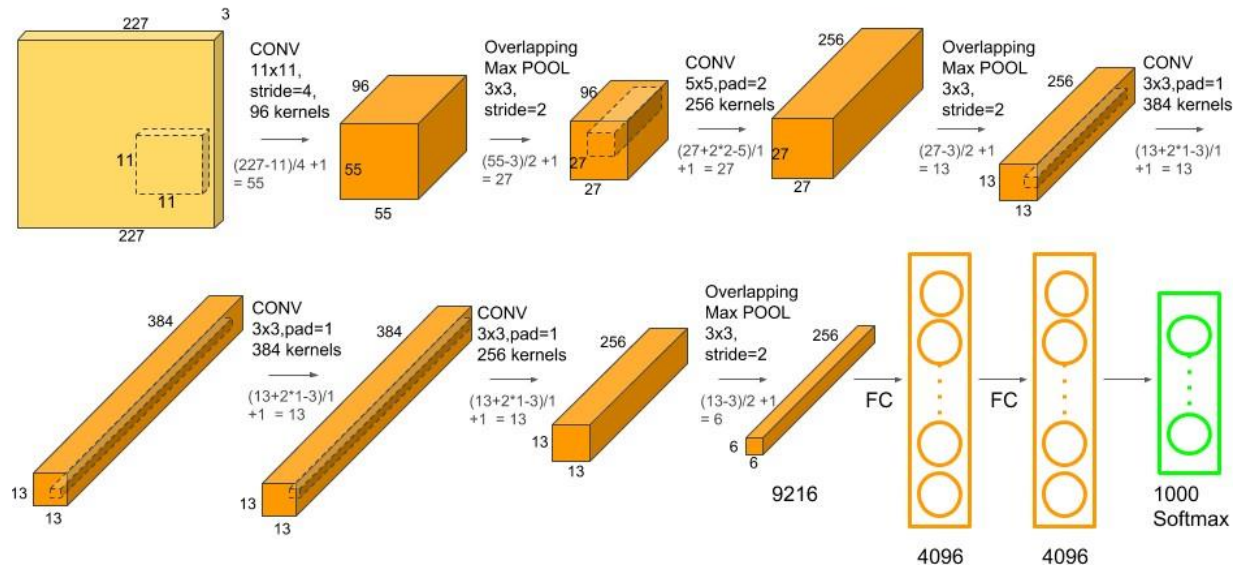


Fig 5.2.1.1 AlexNet

5.2.1.2 ResNet50: A 50-layer residual network that addresses the vanishing gradient problem in deep networks, allowing the training of deeper models with improved accuracy.

- **Strengths:** ResNet50 excels in capturing intricate patterns in skin lesion images due to its depth.
- **Limitations:** Higher computational cost compared to simpler models.

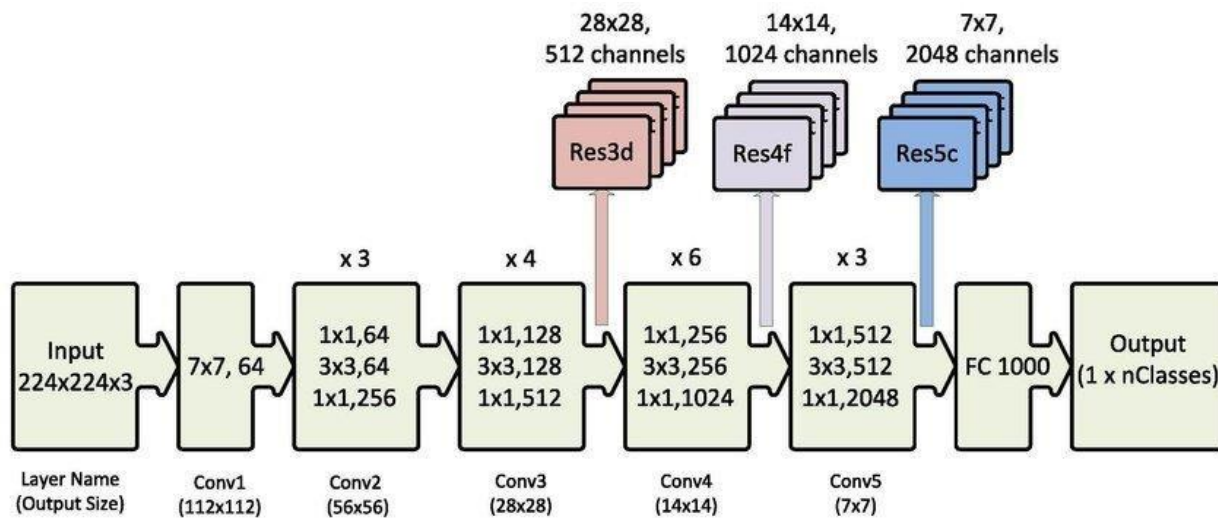


Fig 5.2.1.2 ResNet50

5.2.1.3 VGG16 and VGG19: These deep CNNs use small convolutional filters but have a large number of layers (16 and 19, respectively), making them highly effective for image classification tasks.

- **Strengths:** VGG models capture fine details and are highly accurate in image classification.
- **Limitations:** They require more computational resources and are slower compared to other models like ResNet.

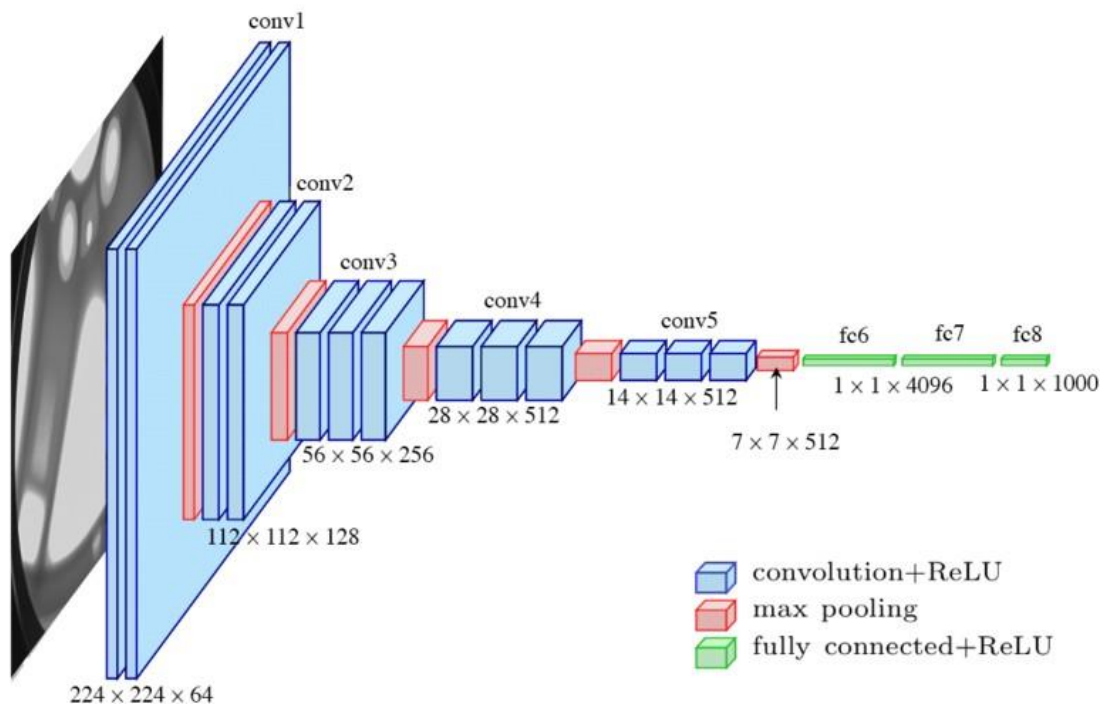


Fig 5.2.1.3.a Visual Geometry Group 16

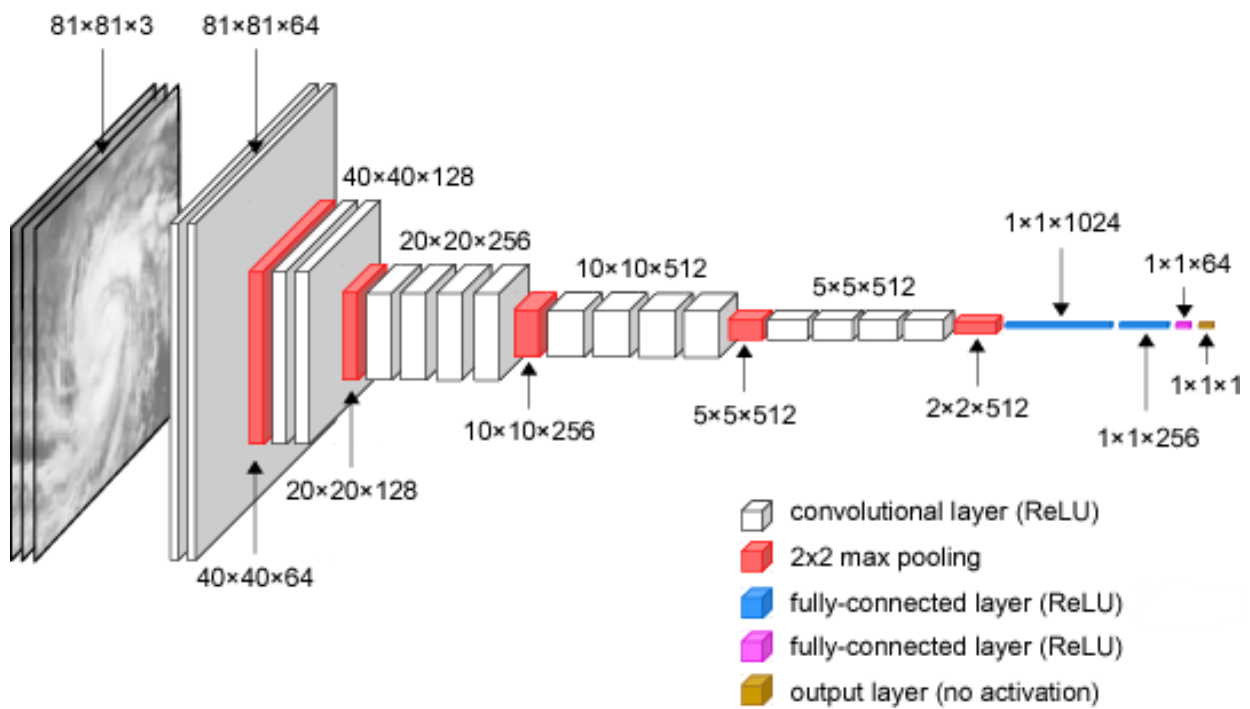


Fig 5.2.1.3.b Visual Geometry Group 19

Chapter 6

SYSTEM IMPLEMENTATION

6.1 MODULE 1: DATA COLLECTION AND PREPROCESSING

6.1.1 Data Collection

For melanoma detection, the system requires a large dataset of dermatoscopic images. These images are categorized into two classes: **melanoma** and **non-melanoma**. The dataset can be sourced from publicly available medical image repositories such as the **International Skin Imaging Collaboration (ISIC)** dataset, which contains thousands of annotated images for training machine learning models.

- **Types of Data:**

- **Dermatoscopic Images:** High-resolution images of skin lesions, labeled as melanoma or non-melanoma.
- **Metadata:** Additional information such as patient demographics (age, gender), lesion location, and diagnostic outcomes (e.g., biopsy results).

- **Steps for Data Collection:**

1. **Access Datasets:** Download images from repositories like ISIC.
2. **Annotation:** Ensure that the images are labeled accurately (melanoma or non-melanoma) to facilitate supervised learning.

6.1.2 Data Preprocessing

Once the dataset is collected, it needs to be reprocessed to ensure that the images are in a format suitable for training the deep learning models. Preprocessing also helps improve model accuracy by removing noise and augmenting the dataset to create more robust training examples.

- **Steps for Data Preprocessing:**

1. **Image Resizing:** Since deep learning models require fixed-size inputs, all images are resized (e.g., 224x224 pixels for models like VGG16 and ResNet50).
2. **Normalization:** Pixel values are scaled to a range (typically [0,1] or [-1,1]) to ensure consistent data representation across all images.
3. **Image Augmentation:** Augmentation techniques are applied to artificially increase the size of the dataset by generating new samples. Techniques include:
 - **Flipping** (horizontal/vertical)
 - **Rotation** (e.g., 15, 30, 45 degrees)
 - **Brightness and Contrast Adjustment**
 - **Zooming and Cropping**
 - **Noise Addition:** Random noise is introduced to simulate variations in image quality.
4. **Splitting the Dataset:** The data is split into three sets:
 - **Training Set:** 70% of the data, used for training the model.
 - **Validation Set:** 15% of the data, used for hyperparameter tuning and preventing overfitting.
 - **Test Set:** 15% of the data, used for final evaluation of the model's performance.

6.1.3 Data Storage and Loading

The preprocessed images are stored in a structured directory, with separate folders for the melanoma and non-melanoma classes. Efficient data loading mechanisms, such as TensorFlow's "**ImageDataGenerator** or PyTorch's **DataLoader**", are used to feed batches of images into the model during training.

6.2 MODULE 2: MODEL TRAINING

After preprocessing, the next step is training the machine learning models on the dermoscopic images. This involves choosing the appropriate model architecture, tuning hyperparameters, and optimizing the model to achieve high accuracy in detecting melanoma.

6.2.1 Model Selection

Deep learning models, particularly **Convolutional Neural Networks (CNNs)**, are chosen for image classification tasks like melanoma detection. The following pre-trained models are used in this project:

- **AlexNet:** A fast and simple CNN architecture, good for quick testing and initial model evaluation.
- **ResNet50:** A deep residual network that helps avoid the vanishing gradient problem, making it ideal for capturing complex patterns in medical images.
- **VGG16 and VGG19:** Deep networks with small convolutional filters, known for their accuracy in large-scale image classification.

6.2.2 Transfer Learning

Since training deep learning models from scratch requires large amounts of data and computational resources, **transfer learning** is employed. Transfer learning allows the system to use models pre-trained on large datasets like **ImageNet**, which are then fine-tuned for melanoma detection.

Steps in Transfer Learning:

1. **Load Pre-Trained Model:** Load a pre-trained CNN (e.g., ResNet50, VGG16) with the weights from ImageNet.
2. **Replace Final Layer:** Modify the final fully connected layer to output two classes (melanoma, non-melanoma) instead of the original 1000 classes in ImageNet.
3. **Freeze Lower Layers:** Freeze the weights of the earlier layers to retain the learned features and only fine-tune the higher layers (fully connected layers).

4. **Fine-Tuning:** Train the model on the melanoma dataset by adjusting the parameters in the upper layers.

6.2.3 Training Process

The model is trained using the training data, and its performance is validated using the validation set.

The following steps are involved in the training process:

1. **Input Data:** Preprocessed images are fed into the model in batches.
2. **Forward Pass:** The model makes predictions on the input data by passing the image through several layers (convolutional, pooling, fully connected).
3. **Loss Function:** The model uses a loss function (e.g., **binary cross-entropy**) to measure the error between predicted and actual labels.
4. **Backpropagation:** The gradients of the loss with respect to each model parameter are computed, and the model updates its weights using an optimizer like **Adam** or **SGD**.
5. **Evaluation on Validation Set:** After each epoch, the model's performance is evaluated on the validation set to monitor overfitting and adjust hyperparameters accordingly (e.g., learning rate, batch size).

The model is trained for several epochs, and the training process continues until the model achieves high accuracy and low loss on the validation set.

6.3 MODULE 3: PREDICTION OF OUTPUT

After training the model, the next step is to deploy it for real-time melanoma detection. The model is integrated into a system where users (e.g., dermatologists) can upload images and receive instant diagnostic results.

6.3.1 Image Upload

Users upload dermoscopic images of skin lesions via a web-based interface. The image is first preprocessed (resized, normalized) and passed to the trained model for prediction.

6.3.2 Model Inference

- The preprocessed image is fed into the trained CNN model.
- The model performs **inference** by processing the image through its layers, extracting features, and making a prediction.
- The final output is a **probability score** for each class (melanoma or non-melanoma). The class with the higher score is selected as the final diagnosis.

6.3.3 Output and Confidence Score

- **Diagnosis Result:** The model returns the classification result (melanoma or non-melanoma).
- **Confidence Score:** Along with the diagnosis, the model provides a confidence score indicating how certain it is of the prediction (e.g., 95% confidence that the lesion is melanoma).

The results are displayed on the user interface in a comprehensible format for the healthcare provider. If necessary, a diagnostic report is generated for future reference or integration into the patient's medical records.

6.3.4 Feedback and Continuous Improvement

Users can provide feedback on the predictions (e.g., if the prediction was accurate based on biopsy results). This feedback is used to continually fine-tune the model and improve its accuracy over time.

Chapter 7

SYSTEM TESTING

7.1 BLACK BOX TESTING

During this kind of testing, the user does not have access to or knowledge of the internal structure or specifics of the data item being tested. In this method, test cases are generated or designed only based on the input and output values, and prior knowledge of either the design or the code is not necessary. The testers are just conscious of knowing about what is thought to be able to do, but they do not know how it is able to do it.

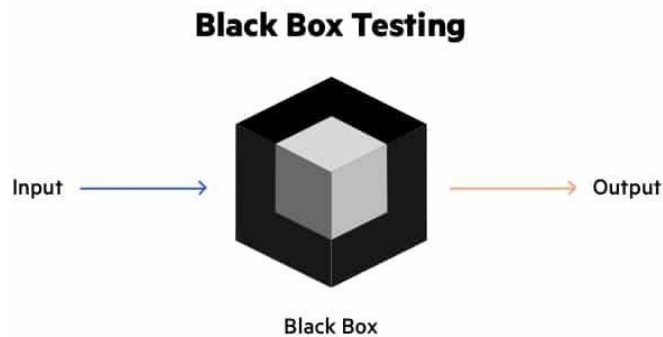


Fig 7.1 Black Box Testing

For example, without having any knowledge of the inner workings of the website, we test the web pages by using a browser, then we authorize the input, and last, we test and validate the outputs against the intended result.

7.2 WHITE BOX TESTING

During this kind of testing, the user is aware of the internal structure and details of the data item, or they have access to such information. In this process, test cases are constructed by referring to the code. Programming is extremely knowledgeable of the manner in which the application of knowledge is significant. White Box Testing is so called because, as we all know, in the tester's eyes it appears to be a white box, and on the inside, everyone can see clearly. This is how the testing got its name.

WHITE BOX TESTING APPROACH

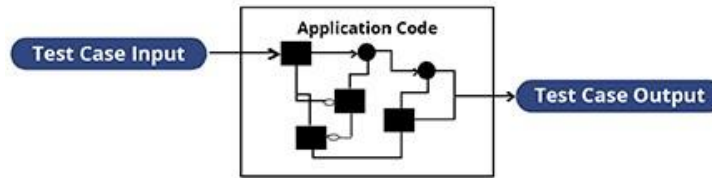


Fig 7.2 White Box Testing

As an instance, a tester and a developer examine the code that is implemented in each field of a website, determine which inputs are acceptable and which are not, and then check the output to ensure it produces the desired result. In addition, the decision is reached by analyzing the code that is really used.

7.3 TEST CASES

TEST REPORT: 01

PRODUCT: Melanoma Detection Using Machine Learning Techniques

USE CASE: Upload Dermatoscopic Image for Melanoma Detection

TEST CASE ID	TEST CASE/ ACTION TO BE PERFORMED	EXPECTED RESULT	ACTUAL RESULT	PASS/FAIL
01	User uploads a dermatoscopic image for analysis.	Image successfully uploaded and preprocessed (resized, normalized).	Image uploaded and processed without errors.	PASS

Table-7.3.1 Test Case For Image Upload

TEST REPORT: 02

PRODUCT: Melanoma Detection Using Machine Learning Techniques

USE CASE: Detect Melanoma and Provide Diagnostic Alert

TEST CASE ID	TEST CASE/ ACTION TO BE PERFORMED	EXPECTED RESULT	ACTUAL RESULT	PASS/FAIL
01	System detects and classifies the uploaded image as melanoma or non-melanoma.	Correct diagnosis of melanoma or non-melanoma based on image analysis.	System provided accurate classification based on training data.	PASS
02	System generates and displays a diagnostic report.	Diagnostic report generated with classification and confidence score.	Report displayed with correct details.	PASS

Table-7.3.2 Test Case For Classifying and Diagnostic Report
Chapter 8

CONCLUSION AND FUTURE ENHANCEMENT

8.1 CONCLUSION

In conclusion, the Melanoma Detection Using Machine Learning Techniques project has successfully demonstrated the potential of using deep learning models to assist in the early detection of melanoma, one

of the deadliest forms of skin cancer. Through the application of advanced image processing techniques and pre-trained Convolutional Neural Networks (CNNs) such as AlexNet, ResNet50, VGG16, and VGG19, the system was able to classify dermoscopic images into melanoma and non-melanoma categories with high accuracy and efficiency.

The system's **data preprocessing** techniques, including image augmentation and normalization, ensured that the input data was of high quality, which significantly improved the performance of the models. By leveraging **transfer learning**, the project reduced the computational and time costs of training from scratch while still achieving excellent results.

This system serves as a valuable tool for healthcare professionals, providing a **real-time diagnosis** that can supplement traditional clinical methods. It helps reduce the time taken for manual analysis of skin lesions, minimizes human error, and enhances the decision-making process. With the ability to process large volumes of data quickly, this system has the potential to scale and be deployed in both urban and rural healthcare settings, where access to dermatological expertise may be limited.

While the system achieved high levels of **accuracy, precision, and recall**, certain limitations such as the dependency on the availability of high-quality datasets and computational resources still exist. Nonetheless, the project's results indicate that machine learning-based systems can make a meaningful contribution to the healthcare domain by offering a non-invasive, efficient, and scalable solution for skin cancer detection.

8.2 FUTURE ENHANCEMENT

Although the current system has shown promising results, there are several areas where future enhancements could be implemented to further improve the performance, scalability, and usability of the system:

8.2.1 Multi-Class Classification

Currently, the system is designed to classify lesions into two categories: **melanoma** and **non-melanoma**. Future work could extend this to a **multi-class classification system** that can identify and distinguish between various types of skin lesions, such as **basal cell carcinoma, squamous cell**

carcinoma, and **benign moles**. This would provide a more comprehensive diagnostic tool for dermatologists, covering a wider range of skin conditions.

8.2.2 Real-Time Mobile Application

Developing a **mobile application** that allows users to take pictures of skin lesions using their smartphone cameras and receive immediate diagnostic results would significantly enhance the system's accessibility. Such a mobile application would particularly benefit patients in remote or underserved areas, offering a convenient and portable solution for early melanoma detection.

8.2.3 Integration with Electronic Health Records (EHR) Systems

Integrating the melanoma detection system with **Electronic Health Record (EHR)** systems would enable seamless storage and retrieval of patient data, including diagnostic images and results. This would improve the workflow for healthcare providers, allowing them to view a patient's history and previous diagnoses more easily while keeping a detailed medical record of all skin lesion assessments.

8.2.4 Incorporating Explainability in AI

While the current system provides accurate predictions, it lacks the ability to **explain** its decision-making process in a human-understandable way. Incorporating **Explainable AI (XAI)** techniques would allow healthcare professionals to understand why the system made a particular diagnosis, increasing trust and transparency in AI-based systems. By highlighting the specific features or regions in the image that led to the diagnosis, clinicians would have greater confidence in the system's recommendations.

8.2.5 Expanding the Dataset for Improved Generalization

Although the system performs well on the dataset used, there is always room for improvement when it comes to **dataset size and diversity**. Expanding the dataset to include images from various ethnicities, age groups, and different lighting conditions would improve the model's generalization ability, making it more robust in real-world scenarios. Collaborating with hospitals, research institutions, and global organizations could facilitate access to larger, more varied datasets.

8.2.6 Improved Model Efficiency

Deep learning models like **ResNet50** and **VGG16** are highly accurate but computationally expensive. In the future, **model optimization techniques** like **quantization**, **pruning**, and

knowledge distillation could be employed to reduce the model size and inference time without sacrificing accuracy. This would allow the system to run efficiently on devices with limited resources, such as mobile phones or edge devices, enabling broader deployment.

8.2.7 Cloud-Based Implementation for Scalability

Deploying the melanoma detection system on a **cloud-based infrastructure** would make the system more scalable, enabling it to handle large numbers of image uploads and diagnoses in parallel. A cloud-based solution would also allow healthcare institutions to use the system without needing to invest in high-end hardware, making it more accessible and cost-effective.

8.2.8 Continuous Learning with Feedback Loops

Incorporating a **feedback loop** mechanism where the system can learn from its mistakes based on user feedback could enhance model performance over time. For example, if a dermatologist corrects a misdiagnosis, this feedback could be used to retrain and fine-tune the model. This approach would result in a continuously improving system that evolves with more real-world use cases.

Chapter 9

APPENDIX 1 – SAMPLE CODING

Final_notebook.ipynb

```
# import packages for data cleaning and visualization
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
%matplotlib inline
plt.style.use('seaborn')
import seaborn as sns

# import packages for image processing and management
import pydicom as dicom
from random import randint
import os, sys, time, shutil, scipy, cv2, json, datetime, pydicom
from tqdm.notebook import tqdm
from skimage import io
from glob import glob
import albumentations as A
from PIL import Image
from skimage.color import label2rgb
import random

import warnings
warnings.simplefilter("ignore")

# import packages for modeling
```

```

import tensorflow as tf

from tensorflow.keras import models, layers, regularizers, optimizers, Sequential, Model

from tensorflow.keras.models import load_model

from tensorflow.keras.layers import Dense, Activation, Flatten, Dropout, BatchNormalization,
Conv2D, MaxPooling2D

from tensorflow.keras.preprocessing.image import ImageDataGenerator

from tensorflow.keras.optimizers import Adam

from tensorflow.keras.callbacks import ModelCheckpoint, EarlyStopping,
ReduceLROnPlateau

from tensorflow.keras.applications.vgg16 import VGG16

from sklearn.model_selection import train_test_split

```

```

# Upload 2019 Training metadata to determine any additional instances of minority class
train19a = pd.read_csv('data/ISIC_2019_Training_GroundTruth.csv')
train19b = pd.read_csv('data/ISIC_2019_Training_Metadata.csv')
train19a = train19a.rename(columns={'image':'image1'})
train19b = train19b.rename(columns={'image':'image2'})
train19 = pd.concat([train19b, train19a], axis=1)
train19 = train19.drop(columns=['image1', 'NV', 'BCC', 'AK', 'BKL', 'DF', 'VASC', 'SCC',
'UNK'], axis=1)
train19.columns = ['file', 'age', 'site', 'lesion_id', 'gender', 'target']
train19.target = train19.target.astype(int)
train19.head()

```

```

# join 2019 and 2020 metadata dataframes
train19_mel = train19[train19.target == 1]
train = pd.concat([train20, train19_mel], axis=0, ignore_index=True)
train.head()

```

```
# display difference in gender distribution of melanoma vs. non-melanoma patients
def twoplots(data1, data2, xlabel, ylabel, title1, title2):
    plt.style.use('ggplot')
    f, (ax1, ax2) = plt.subplots(1, 2, figsize=(12, 4))
    a = sns.countplot(x=xlabel, data=data1, ax=ax1)
    b = sns.countplot(x=xlabel, data=data2, ax=ax2)
    ax1.set_title(title1, fontsize=16)
    ax2.set_title(title2, fontsize=16)
    ax1.set_xlabel(xlabel, size=16)
    ax1.set_ylabel(ylabel, size=16)
    ax2.set_xlabel(xlabel, size=16)
    ax2.set_ylabel(ylabel, size=16)

twoplots(train[train.target == 0], train[train.target == 1], 'gender', 'count', "Gender Distribution
of Non-Melanoma Patients", "Gender Distribution of Melanoma Patients")
```

```
# display distribution of age for non-melanoma vs. melanoma patients
f, (ax1, ax2) = plt.subplots(1, 2, figsize=(12, 4))
sns.histplot(x='age', data=train[train.target == 0], kde=True, color='dodgerblue', ax=ax1)
sns.histplot(x='age', data=train[train.target == 1], kde=True, color='tomato', ax=ax2)
ax1.set_title("Age Distribution of Non-Melanoma Patients", fontsize=16)
ax2.set_title("Age Distribution of Melanoma Patients", fontsize=16)
ax1.set_xlabel('Age', size=16)
ax1.set_ylabel('Count', size=16)
ax2.set_xlabel('Age', size=16)
ax2.set_ylabel('Count', size=16)
```

```
# display distribution of age between training and testing datasets
test.age = test[~test.age.isna()].age.astype(int)
```

```

f, (ax1, ax2) = plt.subplots(1, 2, figsize=(12, 4))
sns.histplot(x='age', data=train, kde=True, color='dodgerblue', ax=ax1)
sns.histplot(x='age', data=test[~test.age.isna()], kde=True, color='tomato', ax=ax2)
ax1.set_title("Age Distribution of Training Set", fontsize=16)
ax2.set_title("Age Distribution of Testing Set", fontsize=16)

# visualization for site distributions for melanoma vs. non-melanoma patients
train2 = train.copy()
train2["site"].replace({"anterior torso": "torso", "lateral torso": "torso", "posterior torso":
"torso"}, inplace=True)
f, (ax1, ax2) = plt.subplots(1, 2, figsize=(14, 6))
a = sns.countplot(x='site', data=train2[train2.target == 0], order = train2[train2.target ==
0]['site'].value_counts().index, ax=ax1)
b = sns.countplot(x='site', data=train2[train2.target == 1], order = train2[train2.target ==
1]['site'].value_counts().index, ax=ax2)
ax1.set_title("Site Distribution of Non-Melanoma Patients", fontsize=16)
ax2.set_title("Site Distribution of Melanoma Patients", fontsize=16)
for p in a.patches:
    a.annotate(p.get_height(), (p.get_x() + p.get_width() / 2., p.get_height()),
               ha = 'center',
               va = 'center',
               xytext = (0,10),
               textcoords = 'offset points')
for p in b.patches:
    b.annotate(p.get_height(), (p.get_x() + p.get_width() / 2., p.get_height()),
               ha = 'center',
               va = 'center',
               xytext = (0,10),
               textcoords = 'offset points')
for ax in f.axes:
    plt.sca(ax)
    plt.xticks(rotation=45, fontsize=16, ha='right')

```

```

# create bar graph of diagnosis of all patients ordered by decreasing count
train_diag = train[train.diagnosis != 'unknown']
g = sns.countplot(x='diagnosis', data=train_diag)
for p in g.patches:
    g.annotate(p.get_height(), (p.get_x() + p.get_width() / 2., p.get_height()),
               ha = 'center',
               va = 'center',
               xytext = (0,10),
               textcoords = 'offset points')
plt.title("Diagnosis of Patients Presenting Lesions", fontsize=16)
plt.xticks(rotation=45, fontsize=16, ha='right')

```

```

# display first ten images in the melanoma subfolder of training dataset folder
paths = glob('split/train/mel/*.jpg')
fig, axes = plt.subplots(nrows=2, ncols=5, figsize=(16,6))
plt.suptitle('Melanoma Images', fontsize=16)
for i in range(0, 10):
    image = cv2.imread(paths[i], cv2.IMREAD_COLOR)
    image = cv2.cvtColor(image, cv2.COLOR_BGR2RGB)
    image = cv2.resize(image, (256,256))
    x = i // 5
    y = i % 5
    axes[x, y].imshow(image, cmap=plt.cm.bone)
    axes[x, y].axis('off')

```

```

# display first ten images in the non-melanoma subfolder of training dataset folder
paths = glob('split/train/not_mel/*.jpg')
fig, axes = plt.subplots(nrows=2, ncols=5, figsize=(16,6))
plt.suptitle('Non-Melanoma Images', fontsize=16)

```

```

for i in range(0, 10):
    image = cv2.imread(paths[i], cv2.IMREAD_COLOR)
    image = cv2.cvtColor(image, cv2.COLOR_BGR2RGB)
    image = cv2.resize(image, (256,256))
    x = i // 5
    y = i % 5
    axes[x, y].imshow(image, cmap=plt.cm.bone)
    axes[x, y].axis('off')

# display transformations of the first ten images in the melanoma subfolder in training dataset
folder

transform = A.Compose([
    A.HueSaturationValue(hue_shift_limit=10, sat_shift_limit=20, val_shift_limit=10)
])

paths = glob('split/train/mel/* .jpg')
fig, axes = plt.subplots(nrows=2, ncols=5, figsize=(16,6))
plt.suptitle('HueSaturationValue', fontsize=16)
for i in range(0, 10):
    image = cv2.imread(paths[i], cv2.IMREAD_COLOR)
    image = cv2.cvtColor(image, cv2.COLOR_BGR2RGB)
    image = cv2.resize(image, (256,256))
    transformed = transform(image=image)
    aug_image = transformed['image']

    x = i // 5
    y = i % 5
    axes[x, y].imshow(aug_image, cmap=plt.cm.bone)
    axes[x, y].axis('off')

```

```

# define test generator for predicting
test_fldr = 'jpegs/split/test'
test_generator = ImageDataGenerator(rescale=1./255).flow_from_directory(
    test_fldr,
    target_size = (224, 224),
    batch_size = 1,
    class_mode = 'binary',
    seed = 42,
    shuffle = False)
STEP_SIZE_TEST = test_generator.n // test_generator.batch_size

test_fldr_2 = 'jpegs/split/test2'
test_generator_2 = ImageDataGenerator(rescale=1/255).flow_from_directory(
    test_fldr_2,
    target_size = (224, 224),
    batch_size = 1,
    class_mode = 'binary',
    shuffle = False,
    seed = 42)
STEP_SIZE_TEST_2 = test_generator_2.n // test_generator_2.batch_size

```

app.py:

```

import os
import glob
import tensorflow as tf
from flask import Flask, render_template, request, send_from_directory
from keras.preprocessing.image import ImageDataGenerator, load_img, img_to_array

```

```

app = Flask(__name__)

# Folder paths
dir_path = os.path.dirname(os.path.realpath(__file__))
UPLOAD_FOLDER = os.path.join(dir_path, "uploads", "all_class")
STATIC_FOLDER = os.path.join(dir_path, "static")
os.makedirs(UPLOAD_FOLDER, exist_ok=True)

# Load the model from the static folder
model = tf.keras.models.load_model(os.path.join(STATIC_FOLDER, "model.h5"))

IMAGE_SIZE = 224

# Function to preprocess uploaded images
def load_and_preprocess_image():
    test_fldr = 'uploads'
    test_generator = ImageDataGenerator(rescale=1./255).flow_from_directory(
        test_fldr,
        target_size=(IMAGE_SIZE, IMAGE_SIZE),
        batch_size=1,
        class_mode=None,
        shuffle=False
    )
    test_generator.reset()
    return test_generator

# Function to classify the uploaded image
def classify(model):
    batch_size = 1
    test_generator = load_and_preprocess_image()

    # Replaced deprecated predict_generator with predict

```

```

prob = model.predict(test_generator, steps=len(test_generator) // batch_size)

labels = {0: 'Just another beauty mark', 1: 'Get that mole checked out'}
label = labels[1] if prob[0][0] >= 0.5 else labels[0]
classified_prob = prob[0][0] if prob[0][0] >= 0.5 else 1 - prob[0][0]

return label, classified_prob

# Home route to clean up old files and render home page
@app.route("/", methods=['GET'])
def home():
    # Clean up old files in the uploads folder
    filelist = glob.glob(os.path.join(UPLOAD_FOLDER, ".*.*"))
    for filePath in filelist:
        try:
            os.remove(filePath)
        except OSError as e:
            print(f"Error while deleting file {filePath}: {e}")

    return render_template("home.html")

# Route to handle file upload and classification
@app.route("/classify", methods=["POST", "GET"])
def upload_file():
    if request.method == "GET":
        return render_template("home.html")

    if "image" not in request.files:
        return render_template("home.html", error="No file part")

    file = request.files["image"]

```

```

if file.filename == "":
    return render_template("home.html", error="No selected file")

# Save the uploaded file
upload_image_path = os.path.join(UPLOAD_FOLDER, file.filename)
file.save(upload_image_path)

# Classify the uploaded image
label, prob = classify(model)
prob = round(prob * 100, 2)

return render_template(
    "classify.html", image_file_name=file.filename, label=label, prob=prob
)

# Route to serve the uploaded image
@app.route("/classify/<filename>")
def send_file(filename):
    return send_from_directory(UPLOAD_FOLDER, filename)

if __name__ == "__main__":
    app.run(host='0.0.0.0', debug=True)

```

Chapter 10

APPENDIX 2 – SAMPLE OUTPUT

10.1 Home Page

The project output screenshots are shown as follows:

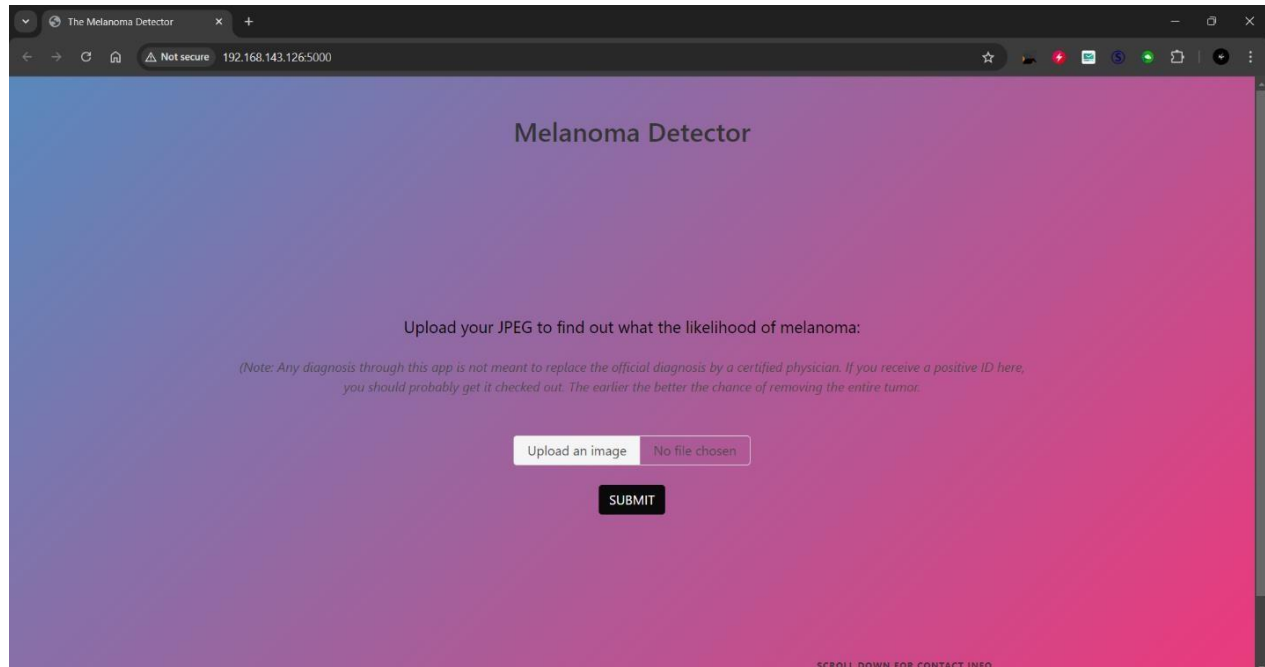


Fig 10.1 Home Page

1. Upload Image Screen

This screen allows users (dermatologists/healthcare professionals) to upload dermoscopic images for analysis. The user interface is designed to be intuitive, ensuring a smooth experience

2. Image Preprocessing Status

Once the image is uploaded, the system preprocesses the image. This screen displays the status of the preprocessing stage, including any augmentation techniques applied.

10.2 Detection with Details

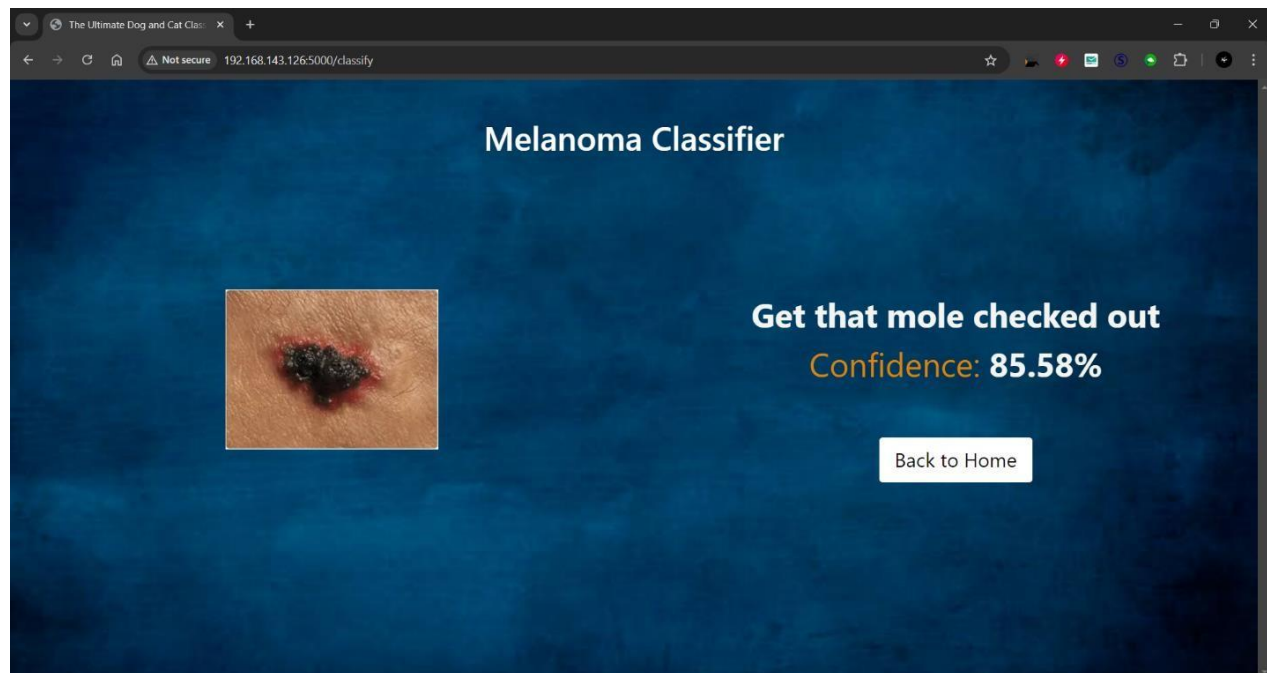


Fig 10.2 Detection with details

1. Diagnosis Result Screen

After the image is processed, the system classifies it and presents the diagnosis. This screen shows the result of the analysis, indicating whether the lesion is melanoma or non-melanoma, along with the confidence score.

2. Diagnostic Report

The diagnostic report summarizes the classification results, confidence levels, and any additional notes. This report can be saved for future reference.

Chapter 11

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