A project report on

Skin Cancer Detection using Deep Learning

Submitted in partial fulfillment for the award of the degree of

Bachelor of Technology in Computer Science and Engineering with Specialization in AI and Robotics

by

VEDANT KISHORE ADKA (21BRS1394)
CHAVALI SAI SREE RAM YADAV (21BRS1359)

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Vellore Institute of Technology
(Deemed to be University under section 3 of UGC Act, 1956)
CHENNAI

SCHOOL OF COMPUTER SCIENCE AND ENGINEERING

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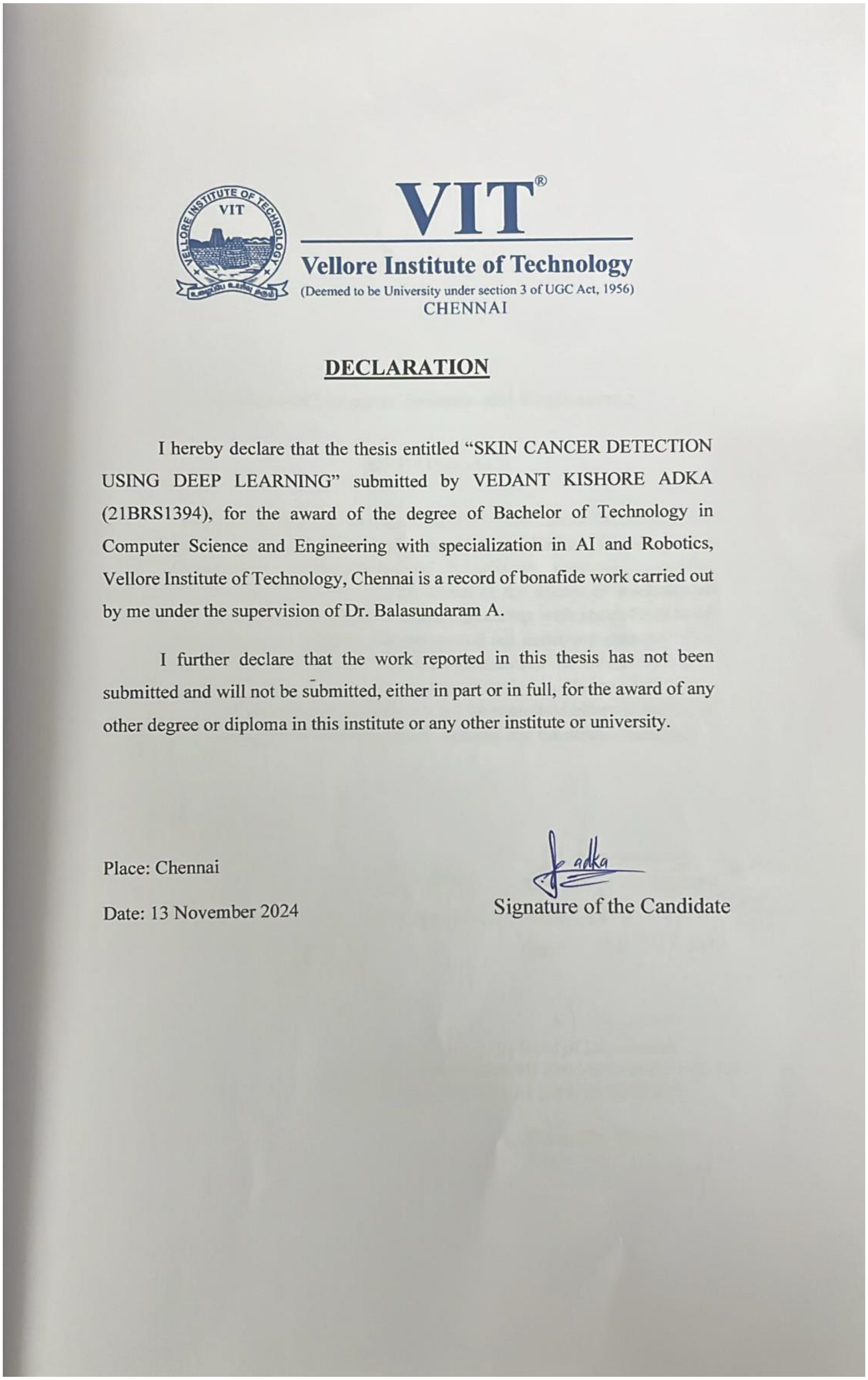

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DECLARATION

I hereby declare that the thesis entitled "SKIN CANCER DETECTION USING DEEP LEARNING" submitted by VEDANT KISHORE ADKA (21BRS1394), for the award of the degree of Bachelor of Technology in Computer Science and Engineering with specialization in AI and Robotics, Vellore Institute of Technology, Chennai is a record of bonafide work carried out by me under the supervision of Dr. Balasundaram A.

I further declare that the work reported in this thesis has not been submitted and will not be submitted, either in part or in full, for the award of any other degree or diploma in this institute or any other institute or university.

Place: Chennai

Date: 13 November 2024

adka

Signature of the Candidate

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This is to certify that the report entitled "Skin Cancer Detection using Deep Learning" is prepared and submitted by Vedant Kishore Adka (21BRS1394) to Vellore Institute of Technology, Chennai, in partial fulfillment of the requirement for the award of the degree of **Bachelor of Technology in Computer Science and Engineering with specialization in AI and Robotics** is a bonafide record carried out under my guidance. The project fulfills the requirements as per the regulations of this University and in my opinion meets the necessary standards for submission. The contents of this report have not been submitted and will not be submitted either in part or in full, for the award of any other degree or diploma and the same is certified.

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Date: 18.11.24

ABSTRACT

As a result of the increasing frequency of skin cancers globally, the time has become ripe for designing enhanced diagnostic methods to be deployed in early detection and better diagnosis of patients. This project aims at designing and implementing an automated deep learning system for benign versus malignant classification of skin lesions. Taking advantage of the capability of the Vision Transformer (ViT) model to capture complex features in images through self-attention mechanisms, this research approaches a new concept for the diagnosis of skin cancer.

It uses the HAM10000 dataset-a broad and exhaustive collection of dermatoscopic images depicting numerous kinds of skin afflictions. Initial data preprocessing includes normalization and resizing of images to ensure it is uniform for model input. Data augmentation techniques-like rotation, flipping, zooming, rescaling-were used with TensorFlow's ImageDataGenerator to enhance generalization and robustness of the models. These steps create a more heterogeneous training set, so overall overfitting is mitigated, and the model's ability to work on unseen data is improved.

The ViT architecture is used since it proves to be pretty effective in picking up the local and global patterns of an image by breaking the image into patches and using a self-attention mechanism. Using this, the model can contextualize its analysis over image parts, increasing classification accuracy. During training, the Adam optimizer and cross-entropy loss have been used along with early stopping and learning rate scheduling to control overfitting and optimize learning. Evaluating the model's performance includes some primary metrics-the accuracy, precision, recall, F1-score, and a confusion matrix that provides detailed insight into the actual strength points and possible biases in the classification.

This project holds significant promise for real-world applications, especially in telemedicine. Deploying the system on telemedicine platforms can provide rapid, automated diagnostic support to healthcare providers and patients, facilitating timely decision-making and treatment. By addressing challenges in early skin cancer detection, this project aims to reduce diagnostic delays, enhance healthcare accessibility, and contribute to better patient outcomes. The research further highlights the potential of advanced deep learning models like Vision Transformers in revolutionizing medical diagnostics and shaping the future of AI-driven healthcare solutions

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Place: Chennai

Date: 13 November 2024 **Vedant Kishore Adka**

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List of Abbreviations

Abbreviation	**Full Form**
AI	Artificial Intelligence
CT	Computed Tomography
EDA	Exploratory Data Analysis
FN	False Negatives
FP	False Positives
GAN	Generative Adversarial Network
HAM10000	Human Against Machine with 10,000 training images dataset
MRI	Magnetic Resonance Imaging
MSE	Mean Sensitivity Index
NLP	Natural Language Processing
NV	Melanocytic Nevi
ResNet	Residual Network
SCC	Squamous Cell Carcinoma
SHAP	SHapley Additive exPlanations
TP	True Positives
UV	Ultraviolet

ViT	Vision Transformer

Chapter 1

INTRODUCTION

Skin cancer has emerged as one of the most common cancer diseases in the world, with the increase in incidence frighteningly high, primarily attributed to factors such as increasing exposure time under UV radiation from the sun, the increased usage of tanning beds, and aging populations. While many millions of cases of non-melanoma and hundreds of thousands of melanoma are diagnosed annually, early detection and intervention appear to be urgently needed. Early diagnosis improves significantly the outcome of treatment and enhances survival probabilities with minimal disability and handicap for the patient.

There are mainly three types of skin cancer: basal cell carcinoma, squamous cell carcinoma, and melanoma. Among them, the most common form of skin cancer is BCC, which emerges in basal cells of the skin and grows slowly. In very rare cases, it might extend to other parts of the body, but otherwise, if untreated, it can create havoc locally. SCC develops from squamous cells and is more aggressive compared to BCC. It has higher metastatic potential if it is not treated early. Melanoma is the rarest but deadliest skin cancer because it has a rapid potential for metastasizing to other organs of the body.

Moreover, the fundamental cause of skin cancer development is the damage UV radiation induces on the DNA inside the skin cell; it can result in mutations that lead to the proliferation of cells without regulation. Other predisposing factors include fair skin, sunburn history, excessive use of tanning beds, a weakened immune system, and a family history of skin cancer.

Where, whereas earlier skin cancer diagnosis was done by mere visual examination and biopsy, as that was the hallmark of traditional diagnosis; slow, subjective, prone to human errors, and sometimes causing delayed diagnosis, it has finally come to an end with modern technology, and in particular deep learning, which has opened tremendous vistas for the use of AI in automated diagnosis of skin cancer, and image analysis proves to be exceedingly accurate in determining and identifying malignant lesions.

The Vision Transformer model used in this project is supposed to examine images of skin lesions. The original model, ViT, is the architecture meant for natural language processing application, but it can be used as an image-classifying tool since it has the attention mechanism that is viewing the global and local features in the images. This may make further accurate skin lesion patterns very early on, pointing out cancer and hence early detection.

Actually, the project really aims to integrate deep learning into dermatology to cut down on time used in diagnostics and improve patient outcomes provided by a reliable, automated tool for detecting skin cancer. This is intended to be developed to a level of wide accessibility which makes it more effective in screening where specialist care cannot always be easily accessed.

1.1 Need for Automated Detection in Dermatology: A Skin Cancer Classification Model

The big challenge in the health sector, especially in dermatology is the early detection and diagnosis of skin cancers, yet the commonest cancers amongst mankind today have often not seen medical attention at their earliest stages and instead they have turned worst with higher rates of mortality. The current methods of skin cancer diagnosis usually depend on the manual evaluation and visual inspection by the dermatologists; such traditional methods are time-consuming, subjective, and prone to human error. This would further result in wrongful diagnoses and missed opportunities for early interventions.

Those inefficiencies and the growing call for faster, more accurate diagnostic tools gave birth to automated detection in dermatology, especially the classification of skin cancer. The arrival of AI and ML technology has now made it possible to change the paradigms through which skin cancers can be diagnosed-for higher precision and consistency in identifying malignant lesions in the skin.

The primary motivations for developing a classification model for automated skin cancer are:

1. **Improved Diagnostic Accuracy**: Machine learning models, particularly deep learning techniques, can analyze medical images with greater accuracy and consistency than human clinicians, reducing the risk of misdiagnosis and human error.
2. **Early Surveillance:** Automated machines can automatically recognize early skin cancer signs that might not easily be detected naked and interventions can be done right in time that improves the patient's prognosis.
3. **Scalability:** Automated systems can process a large number of cases, allowing screening to be conducted of more patients in less time, especially in areas where there is a shortfall in the number of dermatologists, and providing for more scalability in early detection.
4. **Reduced Health Load:** The automation of diagnostic processes enables dermatologists to direct efforts toward complicated cases requiring human expert input which aims at making health care delivery efficient in order to reduce the total load on health care.
5. **Accessibility**: Access Create automated diagnosis systems in rural and isolated areas such that patients reach them with minimum travel since they can now access quality diagnostic tools without traveling long distances to see a specialist.
6. **Integration with Telemedicine**: Given the fast growth of telemedicine, an automated model can be integrated with the telehealth platform to offer remote consultation and diagnosis. This move will make dermatological services more accessible to patients across the globe.

The current work focuses on developing an automated classification model for skin cancer based on AI-based deep learning that would help overcome these problems while increasing diagnostic accuracy and appropriate care for patients with improved quality of care in the field of dermatology. The development of an automated skin cancer classification model, driven by AI and deep learning, is crucial in addressing these challenges, enhancing diagnostic accuracy, and ensuring that patients receive timely and effective care, ultimately improving the overall quality of healthcare in dermatology.

1.2 Motivation of the Project

In fact, some of the key enablers of "Advance Skin Cancer Detection using Deep Learning" involve those connected to healthcare outcome and technological advancement. The healthcare outcome is affected adversely since skin cancer is one of the most prevalent preventable cancers. Some treatments are only possible if the disease is diagnosed early. However, the traditional diagnostic methods are very dependent on a clinician in making a visual inspection that could be subjective and prone to errors. That is where technology can intervene to make the diagnostics more reliable and quick.

This project addresses the challenge of these areas, thus contributing to the bigger endeavour of integration of AI into the health sector. Skin cancers are increasing in incidence, and by many accounts, access to specialist care is rapidly becoming restricted in many parts of the world. Fast, precise diagnoses at scale are urgently required.

Key motivating factors for this project include:

1. **Improving Diagnostic Accuracy:** This improves diagnosis accuracy. The use of deep learning models, like ResNet and Vision Transformers, allows for high-precision and consistent skin cancer detection, reducing the human error margin.
2. **Early Detection**: Improves the earlier diagnosis of skin cancer, thereby improving patient care through the enhancement of timely interventions which may assist in averting untimely death.
3. **Increased Access to Healthcare Services:** An accessible, self-service system, to democratize the diagnosis of skin cancer in the underserved areas or geographic locations where specialists may not be readily available.
4. **Adapting to Technological Advancements:** Adoption of Technological Innovation The advent of the AI implementation process in the health sector offers an excellent window for changing diagnostics, making such workflows better, faster, and more efficient.
5. **Reduced Health Burden:** The process of automation of detection releases more expertise of clinicians from dealing with the complex cases to handle more in improving general health efficiency while reducing healthcare burdens.

This project brings technology innovation much closer to health needs through making skin cancer detection more accurate, faster, and accessible in order to contribute to the impactful application of deep learning models in real-world applications.

1.3 Problem Statement

The challenge the project addresses falls in the context of early and accurate detection of skin cancer, because that would determine the successful outcome of curing it. Skin cancer is one of the most common forms of cancer around the world, and its diagnosis and treatment are often made sadly late or inaccurate due to several factors: lack of access to dermatological expertise, complexity of benign versus malignant skin lesions, and the very subjective nature of traditional diagnostic approaches.

Current diagnostic approaches rely heavily on manual examination by dermatologists, which can lead to delays in detection, particularly in regions with limited access to specialized care. Moreover, dermatological assessments are time-intensive, and even minor errors can result in patients either receiving unnecessary treatments or experiencing progression of the disease due to late intervention.

The objective of this project is to address these challenges by developing an AI-driven skin cancer detection system using deep learning techniques. The proposed system aims to:

- Develop an image-based classification of skin lesions into different classes, including malignancies like melanomas and benign lesion classes.
- Provide a rapid, reliable, and accessible diagnostic tool that can assist healthcare providers and enable early intervention, particularly in under-resourced areas.
- Reduce the dependency on human expertise and mitigate diagnostic inconsistencies, thereby ensuring that more patients receive timely, accurate diagnoses.

In the end, it is hoped that this project can increase rates in early detection of skin cancer and also lead to a reduction in the overall healthcare burden with this reliable, automated diagnostic solution harnessed with the power of deep learning.

1.4 Aim and Objectives

Aim:

We are dealing with a project that aims to develop an accurate and robust machine learning model to detect the type of skin cancer by combining the ResNet-50 architecture and Vision Transformer in a hybrid deep learning approach. It essentially intends to improve the diagnosis of skin-cancer cases by attaining greater accuracy through the classification of skin lesions using the HAM10000 dataset.

Objectives:

1. Develop a Hybrid Deep Learning Model:
   Build and train a hybrid model combining ResNet-50 and Vision Transformer (ViT) architectures, leveraging both spatial feature extraction and pattern recognition capabilities to enhance classification accuracy.
2. Preprocess the HAM10000 Dataset:
   Perform data preprocessing and augmentation techniques to ensure high-quality input for training, improving model performance across diverse skin lesion images by addressing factors such as lighting, resolution, and variability in skin tone.
3. Optimize Model Performance:
   Apply regularization techniques like dropout, and optimize hyperparameters to reduce overfitting. This objective focuses on maximizing the model's generalization ability, enabling it to perform accurately across all lesion categories.
4. Model Performance Measurement with Appropriate Metrics:
   Validation of the performance of the model in classification on the HAM10000 dataset would require consideration of accuracy, sensitivity, specificity, and F1-score as the evaluation metrics for its strength or precision in diagnostics..

5. Integrate Feedback for Continuous Improvement: Establish a process to incorporate new data and adjust the model accordingly, allowing for continuous improvement in classification accuracy and adaptability to emerging data patterns in skin cancer diagnosis.

This will then lead to the development of a sophisticated and reliable machine-learning model regarding skin-cancer classification, which may find value in health care AI applications for early detection and diagnosis.

1.5 Research Challenge

The development of a machine learning-based skin cancer detection model presents several research challenges, especially with the focus on creating an efficient model without designing an end-user system. Key challenges encountered include:

1. **Class Imbalance in the Dataset**

   The HAM10000 dataset is highly imbalanced, just like most medical datasets: the categories of skin lesions are seriously underrepresented. This generally leads to biased predictions since the model may learn better to detect the more common classes and struggle with the rarer one. The counter strategies applied to fight this challenge involve methods like over and undersampling and applying class weight adjustments during training to ensure balanced learning for each category of skin lesions**.**

2. **Model and Transformer Selection:**

   Selecting an optimal model architecture that balances accuracy and efficiency posed a challenge. The hybrid approach combining ResNet-50 and Vision Transformer (ViT) was chosen to leverage ResNet-50's ability to capture spatial features and ViT's strength in global feature recognition. However, integrating these architectures effectively to prevent overfitting and maximize performance required extensive experimentation and tuning.

3. **Image Preprocessing for Computational Efficiency:**

   Preprocessing images to reduce computational demands while maintaining accuracy was a critical challenge. The need to optimize image dimensions, resolution, and normalization methods had to be carefully balanced to minimize resource usage without compromising model performance. Techniques such as resizing, data augmentation, and normalization were applied to create a streamlined preprocessing pipeline, reducing the computational load while preserving essential image details.

These challenges highlight the complexity involved in building an efficient, accurate skin cancer detection model.

Chapter 2

BACKGROUND

2.1 Literature Review

Recent In recent breakthroughs in deep learning, the early detection and classification of skin cancer have enhanced significantly using different machine learning techniques that prove more diagnostic accurate to assist in clinical decision-making. Esteva et al. Pursuing greater precision, proposed a model of Convolutional Neural Network (CNN) that could eventually match the accuracy of dermatologists in the classification of skin lesions. This approach shows the potential for consistent assessments with fewer errors of diagnosis using CNNs [1] using large dermoscopic image datasets.

Apart from CNNs, another emerging potential of processing images as sequences of patches with self-attention mechanisms to capture both local and global features is vision transformers. This model is particularly suited for analyzing complex skin lesion patterns. By leveraging the HAM10000 dataset, the integration of ViT into skin cancer detection systems has shown promise in enhancing diagnostic accuracy [2].

However, the scarcity of data is still something against which robust models are trained. Towards that, GANs were used to generate dermoscopic images as described by Zhang et al., thereby applying GANs to augment and expand training datasets with reduced overfitting, thereby improving the generalization of the model. [3].

Transfer learning has also been pivotal in enhancing model performance with limited data. Menegola et al. demonstrated that fine-tuning pre-trained models like ResNet and EfficientNet on specialized dermoscopic datasets led to near-clinical accuracy, highlighting the efficiency of transfer learning in skin lesion classification [4]. Beyond single-modality models, integrating multi-modal data—combining dermoscopic images with patient metadata such as age, sex, and lesion location—has been shown to significantly enhance diagnostic outcomes, allowing for a more holistic analysis of patient profiles [5].

However, critical work on interpretability is required with the deep learning models, like CNNs, since most of them function as "black boxes" and obscure to clinicians the diagnostic processes they use. With these issues in mind, researchers have used techniques such as saliency maps "used by Abdelhafiz et al.". used to highlight critical areas of images that influenced the model's predictions. This approach has improved transparency and clinician trust in AI systems [6]. Ensuring fairness in AI models is equally important, as studies by Han et al. emphasize the need for diverse training datasets to avoid biases, especially in models deployed across different ethnic groups [7].

The use of AI in telemedicine has been another focus area. DocOnTap, for instance, integrates machine learning algorithms with online appointment scheduling to enhance diagnostic accuracy and accessibility in regions with limited healthcare resources. By combining AI with patient engagement tools, this system highlights the potential of digital platforms in democratizing healthcare access [8].

In addition to diagnostic systems, healthcare chatbots have advanced significantly, moving beyond basic symptom checks to provide comprehensive treatment advice. By integrating Multi-Layer Perceptron (MLP) models and advanced NLP techniques, these chatbots can offer holistic recommendations, thereby improving patient interaction and satisfaction [9].

For improving treatment recommendations, collaborative filtering algorithms have been applied to minimize medical errors, particularly in environments with incomplete patient records. In Russia’s healthcare system, this method has been effective in leveraging historical data to enhance prescription accuracy, as highlighted in studies focusing on personalized medicine [10].

Attention mechanisms have also been explored to refine healthcare recommendation systems, as seen in the COGNET-AMO model, which integrates attention layers to personalize prescription suggestions based on patient complaints and treatment objectives. This approach emphasizes the importance of context in improving the relevance of healthcare recommendations [11].

The ERNIE model has extended BERT’s capabilities by adding domain-specific medical knowledge to enhance patient-doctor matching. By improving the semantic understanding of complex medical terminology, this model represents a significant step forward in applying NLP to healthcare settings, enabling more accurate doctor recommendations [12]. These hybrid models combine collaborative filtering techniques with content-based techniques to improve the trustworthiness of recommendation systems. Despite focusing on the preferences of patients and respecting their privacy, this supports patient-centered care that can increase the degree of user satisfaction. [13].

Sentiment analysis of patient reviews has also shown promise in improving disease prediction models. By analyzing patient feedback along with demographic data, researchers have achieved a 95% accuracy rate in recommending specialists, highlighting the role of patient sentiment in refining healthcare delivery [14].

In addressing the high misdiagnosis rates in regions like Pakistan, machine learning-based diagnostic systems that combine diagnostic algorithms with scheduling features have shown potential in improving healthcare outcomes. By integrating AI with user-centric features, these systems offer scalable solutions to regional healthcare challenges [15].

Another innovative approach involves the use of transformer-based chatbot systems to streamline medical consultations. Leveraging Bidirectional Encoder Representations from Transformers (BERT), these chatbots assist healthcare providers by offering quick, accurate diagnostic support, especially beneficial in complex cases such as cancer diagnosis [16].

During the COVID-19 pandemic, the demand for automated healthcare solutions surged, leading to the development of drug recommendation systems utilizing advanced vectorization techniques like TF-IDF and Linear Support Vector Classifier (SVC). These models have been instrumental in providing timely medication suggestions, reducing the risk of improper self-medication [17].

To support online consultations, a hybrid deep learning model using the Deep Kronecker Network (DKN) was developed, applying advanced optimization techniques like Al-Biruni Earth Radius (BER). This model enhances specialist recommendations by analyzing symptom data, thereby improving patient outcomes [18].

In efforts to make health monitoring accessible, chatbots using NLP and machine learning have been deployed to assist users in self-diagnosis and treatment planning. By providing proactive health management tools, these chatbots help reduce the strain on healthcare systems by encouraging preventive care practices [19].

Finally, personalized doctor recommendation systems have evolved to incorporate detailed consultation histories, allowing for improved alignment between patient needs and doctor expertise. This focus on historical data and patient profiles has proven effective in enhancing the precision of healthcare recommendations, ultimately fostering better patient engagement and satisfaction [20].

2.2 Deep Learning-Based Hybrid Model Using CNN and Vision Transformers for Optimizing Skin Cancer Detection

It is a hybrid-based skin cancer detection model that makes use of the most advanced deep learning algorithms to facilitate earlier diagnosis of skin cancer. Typically used in putting together the most common models are Convolutional Neural Networks and Vision Transformers, enhancing the accuracy in classifications of skin lesions towards timely recognition of malignant and benign lesions. The hybrid architecture would take the strengths of the CNNs, which are known to be effective at feature capturing in local areas, and the Vision Transformers, adapted for understanding long-range dependencies in images.

This design, exploiting the comprehensive HAM10000 dataset covering so remarkably diverse dermatoscopic images, is designed to make it a powerful diagnostic tool to assist in the support of dermatologists in actual clinical decision-making. The systems preprocess images into normalized and augmented ones to increase variability and, consequently, the generalization capabilities of the model. Combining CNN and ViT architectures allows the model to analyze complex patterns of lesions of skin conditions in general and, therefore, features an accuracy of diagnosis superior to that based on traditional methods.

Techniques of transfer learning and data augmentation are applied in optimising the training of the model to high performance, even with limited amounts of annotated medical data. Techniques of **Explainable AI (XAI)**, such as saliency maps, are used visually to present the explanation for the predictions made by the model itself, thus increasing the transparency and trust of the model among the healthcare professionals. This approach ensures that the system not only delivers accurate results but also offers interpretability, which is crucial in clinical settings.

Designed with scalability in mind, this deep learning-based solution is suitable for deployment on telemedicine platforms, offering real-time diagnostic support to healthcare providers and patients, especially in remote or underserved areas. By automating the initial screening process, the model helps reduce diagnostic delays, improves early detection rates, and enhances overall patient outcomes.

Furthermore, the system is adaptable to diverse patient populations by incorporating robust data augmentation strategies and multi-modal inputs, addressing the challenges of variability in skin types across different demographics. Ultimately, this project represents a significant advancement in personalized dermatology, optimizing the diagnostic pathway for skin cancer detection and contributing to better healthcare accessibility and patient care across global populations.

2.3 Related Works and Technologies Used

In developing an effective machine learning-based skin cancer detection model, choosing the right techniques and tools is essential for optimizing accuracy and efficiency. Here's an overview of the components used in this project, including the rationale for each selection and their contributions to the project.

1. **Hybrid Deep Learning Model – ResNet-50 and Vision Transformer (ViT)**
   - **Overview:** ResNet-50, a convolutional neural network (CNN), and Vision Transformer (ViT), a transformer-based model for image classification, are combined to leverage their unique strengths. ResNet-50 efficiently captures spatial and local patterns in images, while ViT enables better global feature understanding, especially valuable for the identification of subtle differences between complex skin lesions.
   - **Key Features for the Project:**

        - **Spatial and Global Feature Extraction:** ResNet-50 identifies detailed spatial features like edges and textures, which are critical in skin lesion classification. ViT complements this with global attention mechanisms, improving recognition of complex lesion patterns across images.
        - **Performance and Flexibility:** The hybrid model is designed to handle various lesion types with improved accuracy. Through experimental adjustments in layer integration and hyperparameter tuning, the model's performance is enhanced while keeping computational requirements manageable.

2. **Dataset – HAM10000**
    - **Overview:** The HAM10000 dataset is a widely used dataset for dermatological images containing images across seven categories of skin lesions, such as melanoma, basal cell carcinoma, and benign keratosis. This diversity makes it suitable for training a model that classifies the image into multiple types of skin cancer.
    - **Relevance to the Project:**
        - **Comprehensive Representation of Lesion Types:** The dataset covers various skin cancer types, providing a balanced foundation for training the model.
        - **Data Imbalance Handling:** To address the dataset's class imbalance, techniques like oversampling, class-weight adjustment, and data augmentation are applied, improving the model's ability to learn and generalize across all classes effectively.
3. **Image Preprocessing Pipeline**
    - **Overview:** To reduce the computational load, a preprocessing pipeline is implemented, including resizing, normalization, and augmentation. This pipeline prepares images for efficient processing without compromising the quality of the input data.

- **Key Techniques for the Project:**
  - **Resizing and Normalization:** Images are resized into a standard input shape to conform to the model requirements, and pixel values are normalized, which establishes uniformity and accelerates convergence in the training process**.**
  - **Data Augmentation:** Techniques Adding the transformed data to the training set using rotation, flipping and contrast adjustments, adds more diversity to the training set, thereby minimising overfitting and augmenting robustness of the developed model.

4. **Evaluation Metrics**
   - **Overview:** The performance of the model is assessed through using various evaluation metrics, such as accuracy, sensitivity, specificity, and F1-score. These metrics help measure how good the identification ability of the model is for both cancerous and non-cancerous lesions.
   - **Importance for the Project:**
     - **Accuracy and Sensitivity:** Accuracy provides a general performance measure, while sensitivity is crucial for correctly identifying cancerous lesions.
     - **F1-Score:** This is actually an average of precision and recall, a property important in many medical image applications where the measure of false positives and false negatives should both be optimized.
5. **Programming Environment – Python (Jupyter Notebook)**
   - **Overview:** Python is used mainly because of its wide scope of libraries in machine learning and deep learning, that include TensorFlow, Keras, and OpenCV. This all is instrumental in model implementation and image processing. With Jupyter Notebook, one gets an interactive environment to streamline testing and iteration of model components..
   - **Benefits for the Project:**

    - **Library Support:** Libraries like TensorFlow and Keras facilitate efficient model building and experimentation with neural network architectures.
    - **Interactive Debugging and Visualization:** Jupyter Notebook allows for easy debugging, visualization of model performance, and modification of parameters, making it ideal for iterative development.

Tech Stack Integration:

- **Data Flow and Model Training:** The images from the HAM10000 dataset are preprocessed and fed into the hybrid model architecture for training. The model's predictions are evaluated on various metrics to refine and validate performance.
- **Computational Efficiency:** By optimizing preprocessing and model layers, the project maintains computational efficiency without compromising classification accuracy, ensuring that the model remains accessible for deployment in limited-resource environments.

Conclusion:

This technology stack and methodological approach enable the development of an accurately, computationally efficient skin cancer identification model. The project combines CNN and transformer architectures with robust preprocessing and addresses class imbalance to benefit from advanced deep learning techniques toward developing a reliable tool for the classification of skin cancer. These technologies and techniques, when integrated, provide a foundation for highly accurate lesion detection in clinical settings that may aid in early diagnosis and potential intervention.

Chapter 3

METHODOLOGY

3.1. Detailed Overview of the Dataset

The **Skin Cancer MNIST: HAM10000** dataset is one of the most significant datasets in the field of dermatology for skin cancer detection. This dataset was created to help in developing machine learning models aimed at automating the diagnosis of skin cancer, specifically using images of skin diseases to classify them into benign or malignant. The dataset contains **10,015 dermatoscopic images** of diverse skin lesions consisting of melanoma, basal cell carcinoma, and benign conditions such as nevi and keratosis. It has been done by various clinical institutions and labeled very carefully and categorized in accordance with the real variety found in practice.

The HAM10000 dataset has diversity, ranging from a wide variety of lesion types, which provides a broad foundation for machine learning models to learn from. The dataset can be divided into seven categories of skin lesions: Actinic keratoses (AK), Basal cell carcinoma (BCC), Benign keratosis-like lesions (BKL), Dermatofibroma (DF), Melanoma (MEL), Melanocytic nevi (NV), and Vascular lesions (VASC). Such categories include malignant and benign lesions, with melanoma a form of the deadliest cancer called skin cancer. Distinguishing malignant from benign lesions is also a big challenge, which why the dataset adds worth to early skin cancer research

Along with the images, the dataset is enriched with **metadata**, including patient demographic information such as age, sex, and the anatomical site of the lesion (e.g., back, arm, face). This metadata plays a crucial role in training models for more personalized and context-sensitive predictions, potentially improving the accuracy of AI models, especially when combined with the image data. The availability of both image data and metadata helps researchers build multi-modal systems that can take into account both visual and non-visual features to enhance diagnosis accuracy.

The **HAM10000 dataset** appears in the majority of machine learning and deep learning applications for skin cancer detection, as it is particularly used in training and testing

Convolutional Neural Networks (CNNs) and, more recently, Vision Transformers (ViTs), which are transformed for classifying images of skin lesions into one of the predefined categories. The dataset has served as a benchmark for numerous algorithms and models, providing researchers with a means of checking the performance of various techniques in machine learning, in addition to pointing out areas where improvements are necessary. Researchers commonly use techniques like **transfer learning**, where the pre-trained ResNet or InceptionV3 are fine-tuned on the HAM10000 dataset to improve accuracy in cases of smaller datasets.

In terms of preprocessing data, images from the HAM10000 dataset frequently need to be cleaned and augmented to a considerable extent before being used in machine learning models. Standardized resizing of images to, say, 224x224 pixels; normalizing the pixel values to make sure that they are the same across images; and applying data augmentation methods, for instance, rotation, flipping, and zooming, to artificially increase the size of the dataset, are some of the preprocessing steps. This proves particularly beneficial when working with deep learning models: these techniques help the models generalize well to unseen data and avoid the risk of overfitting.

Despite its many advantages, the **HAM10000 dataset** also presents some challenges. One major concern is **data imbalance**, where certain lesion types, such as melanoma, may be underrepresented compared to benign lesions like nevi or dermatofibromas. This can result in a biased model which overcompensates for the more common lesion types but fails to identify rarer or more dangerous conditions. Oversampling, undersampling, and/or adjustment of class weights could be used by researchers to create a better weighting of the dataset and thus improve their model's performance. Another challenge would be ethnic diversity. While the dataset is likely to represent a more comprehensive range of skin tones in comparison to other populations, it may not capture the diversity that may limit the model's generalization to all skin types. This has raised concerns about the fairness of AI models trained on this dataset, especially when applied to patients from underrepresented demographics.

The **HAM10000 dataset** is publicly available for research purposes, making it one of the most important resources for advancing AI applications in dermatology. It can be accessed via the ISIC Archive or platforms like Kaggle, and is free for use under an open license, encouraging wide adoption in both academic research and industrial applications. This dataset has become a cornerstone for the development of automated diagnostic systems, not only for melanoma but also for other skin conditions, helping bridge the gap in healthcare access, particularly in areas where dermatologists are in short supply.

The dataset is also crucial in the rising field of telemedicine, wherein AI models trained on the HAM10000 dataset are deployed on remote healthcare platforms to assist dermatologists in diagnosing skin conditions from afar. These, then, can revolutionize the healthcare system, particularly in areas that have been underserved due to lack of proper healthcare services, because early diagnosis reduces the time between the presentation of symptoms and the date of medical consultation.

In conclusion, the **Skin Cancer MNIST: HAM10000 dataset** is a comprehensive and invaluable resource for advancing skin cancer detection through AI. It provides a diverse set of images with rich metadata, making it ideal for training machine learning models that can assist healthcare professionals in diagnosing skin lesions accurately and efficiently. Despite these challenges, including data imbalance and requirement for more diverse representation, the dataset continues to play a crucial role in developing automated tools that can enhance early detection, improve patient outcomes, and expand access to dermatological care worldwide.

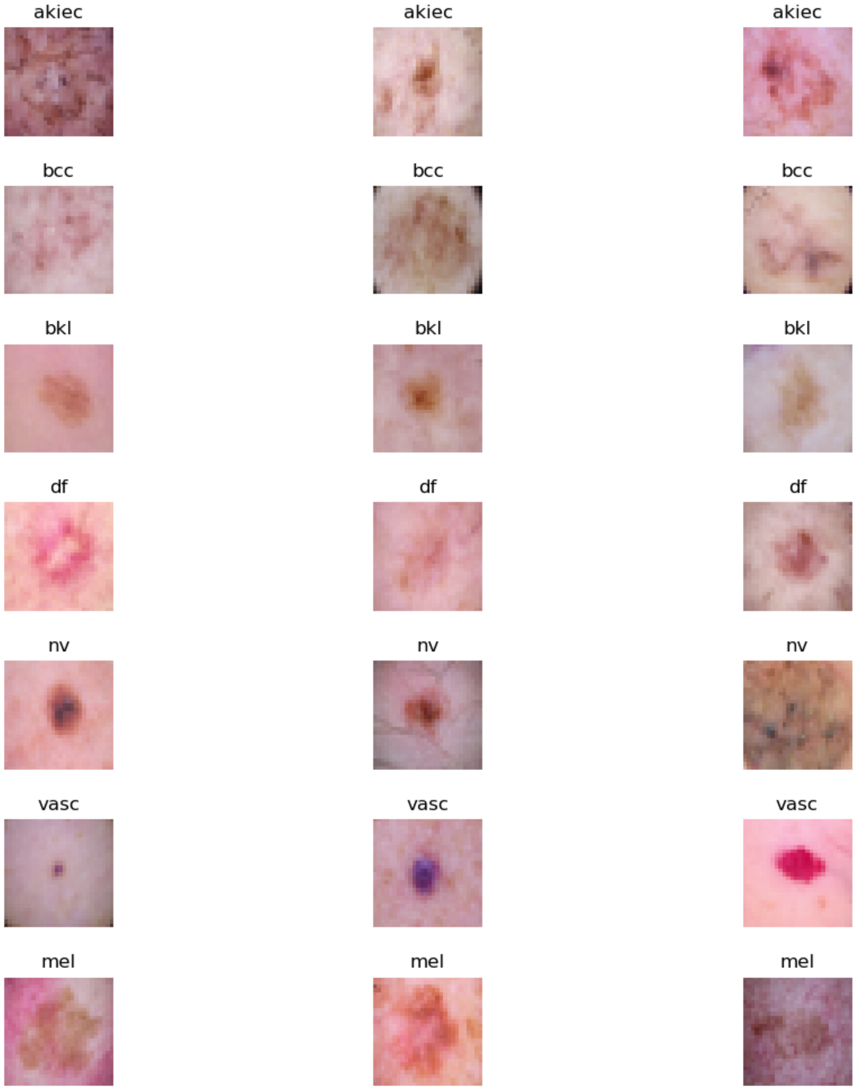


Fig 1. Types of Skin Cancer

3.2. System Architecture Proposal

This section describes the proposed system architecture for melanoma classification, which applies a hybrid model combining ResNet50, which is a Convolutional Neural Network, CNN, along with Vision Transformer, ViT. This hybrid architecture combines the spatial feature extraction benefits of CNNs with the global context capability of transformers to create a model ideally suited for the recognition of fine-grained skin lesion patterns as well as complex textures. Below is a break down of each section and the entire process as shown in the architecture diagram.

Convolutional Neural Network (CNN) and ResNet-50

Overview of CNNs

Convolutional Neural Networks, or CNNs, are deep learning models that are well-suited for image analysis tasks. They process images in a localized manner using convolutional layers to detect edges, textures, and shapes. The hierarchical representation of the image is built by stacking multiple convolutional layers in CNNs, while early layers capture simple patterns and deeper layers the complex patterns. In essence, CNNs are efficient for image processing because they reduce the number of parameters and computations required and leverage techniques like weight sharing and local receptive fields.

Speciality of ResNet and Significance of ResNet-50

ResNet is really the first paper that introduced residual learning in the context of a deep network. Therefore, residual learning is understood as the approach to overcome vanishing gradients by using skip, or shortcut, connections. This essentially enables bypassing some layers in the network, making it easier to learn identity mappings and retain important features from earlier layers. This innovation enables the construction of very deep networks, as ResNet mitigates the degradation problem where accuracy worsens as networks deepen.

ResNet-50 is the 50-layer version of the ResNet model which is quite a regular choice for image classification tasks as a result of its nice balance between depth and computationally efficiency. ResNet-50 has 50 layers in total and thus can capture spatially complex details, but it is also reasonable to train and deploy. There are 4 main blocks, containing multiple convolutional layers with shortcut connections. For this project, ResNet-50 serves as the primary feature extractor, providing a rich set of feature maps that represent the input image's spatial and local patterns.

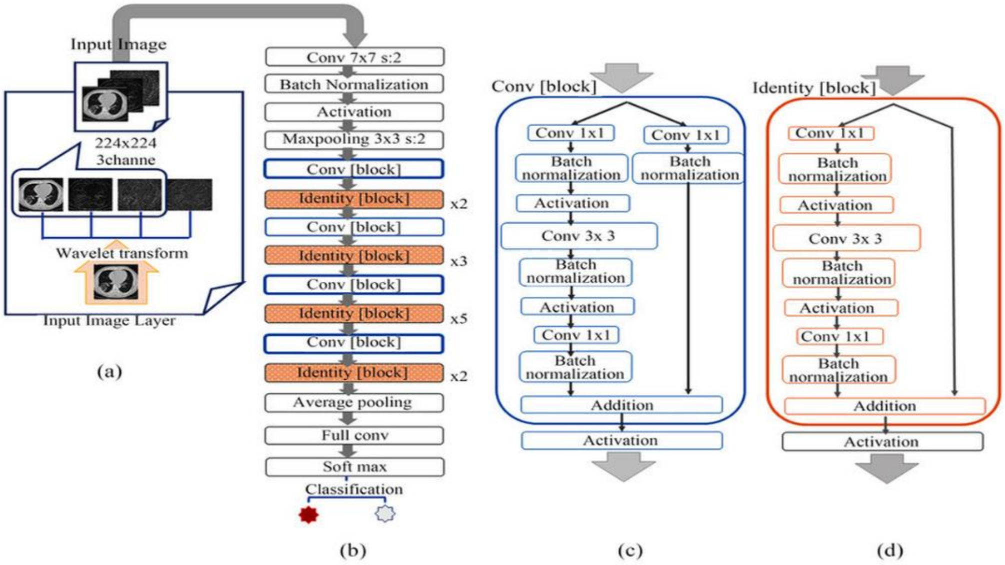


Fig 2. ResNet-50

Vision Transformer (ViT)

Overview of Transformers and the Vision Transformer

Originally designed for Natural Language Processing applications, the self-attention mechanisms within these transformers allow them to capture relations between tokens over long distances; the Application of ViT the Transformer architecture to image data by considering patches of the image to be tokens. By doing so, ViT can capture global dependencies and contextual information across the entire image, which is particularly valuable in tasks where relationships between distant parts of the image matter, as is often the case in medical imaging.

Speciality and Working of the Vision Transformer

The Vision Transformer divides an input image into fixed-size patches, flattens each patch into a 1D vector, and embeds it as a token. Positional embeddings are then added to these tokens to retain spatial information (as transformers do not have a built-in understanding of sequence or spatial position). The transformer encoder processes these tokens using layers of self-attention and feed-forward networks, allowing it to learn relationships across the image globally.

ViT's self-attention mechanism is its core strength, as it enables the model to assign varying levels of importance to different regions of the image, capturing complex patterns that might not be as discernible with convolutional layers alone. In this hybrid model, the ViT complements the ResNet-50's local feature extraction by providing a broader global context.

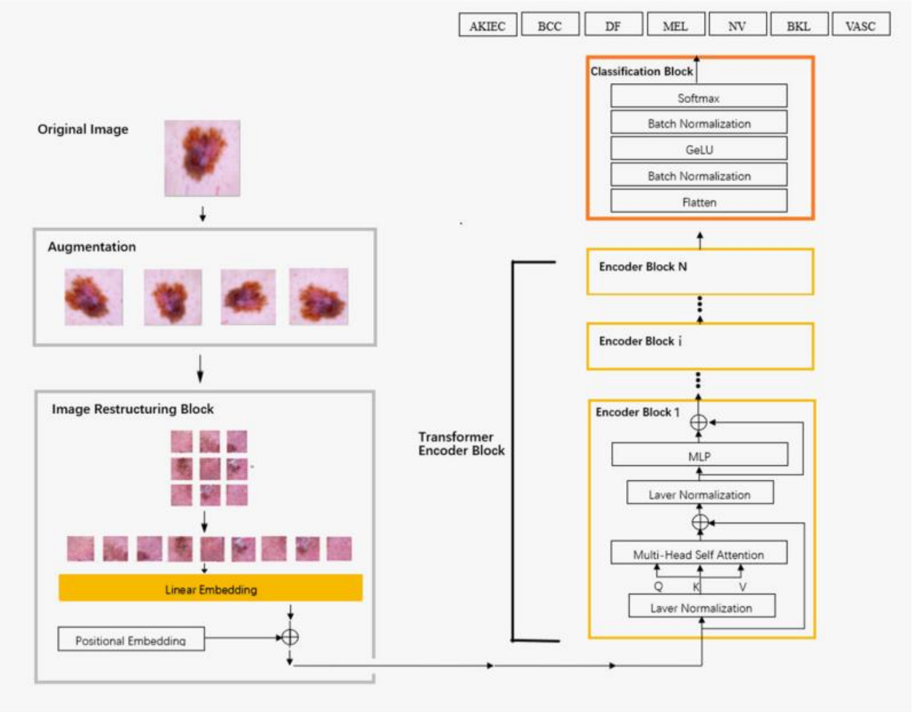


Fig 3. Vision Transformer

3.3Detailed Explanation of the Architecture Diagram

1. Input Image

The model receives an image of shape (256, 256, 3) as input. The dimensions (256, 256) represent the width and height of the image, and 3 channels correspond to the RGB color channels.

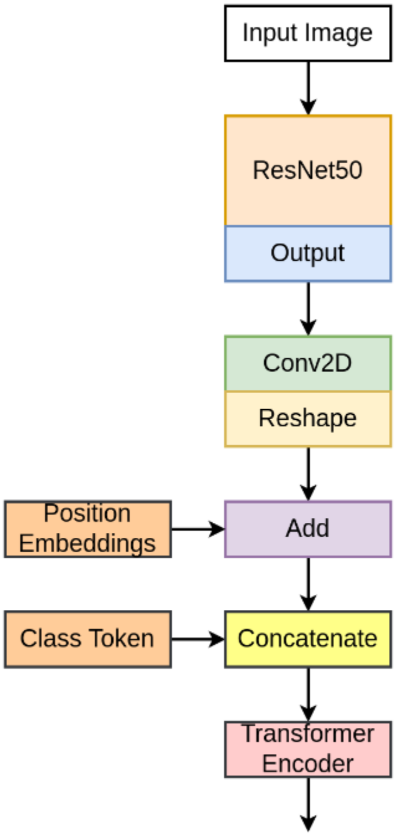


Fig 4. Work Flow of Proposed Model

2. Feature Extraction with ResNet-50

- Feed the input image to a pre-trained ResNet-50 model. Convolutional neural network (CNN) and widely recognized for its efficiency at extracting hierarchical features from images, ResNet-50 has been trained on the ImageNet dataset.
- ResNet-50 consists of several residual blocks that help in capturing various levels of spatial features — from edges and textures in earlier layers to more complex shapes and patterns in deeper layers.
- **Output of ResNet-50**: The output from ResNet-50, with include_top=False (meaning it does not include the fully connected layers at the top), is a feature map of shape (None, 8, 8, 2048). Here, 8 x 8 represents the spatial resolution, and 2048 is the number of feature channels.

3. Patch Embeddings with Conv2D and Reshape

- After feature extraction, the Conv2D layer reduces the number of channels from 2048 to 768 (configurable as hidden_dim) while keeping the spatial dimensions the same (8x8).

- **Output of Conv2D**: The output of this Conv2D layer is of shape (None, 8, 8, 768), where 8x8 is the spatial grid, and 768 is the new channel depth.
- **Reshape**: This feature map is then reshaped to flatten the spatial dimensions, resulting in (None, 64, 768). Here, 64 corresponds to the total number of patches (8 * 8 = 64), and 768 is the embedding dimension of each patch.

4. Position Embeddings

- To give the model information about the position of each patch in the image, **position embeddings** are added to the patch embeddings.
- The position embeddings are generated by an Embedding layer, which produces a tensor of shape (64, 768), representing a unique embedding for each of the 64 patches.
- **Patch + Position Embeddings**: The position embeddings are added to the patch embeddings, resulting in a combined tensor of shape (None, 64, 768).

5. Class Token Addition

- The **Class Token** layer adds a special token to the sequence, which serves as a representation for classification purposes.
- The ClassToken layer initializes a learnable token of shape (1, 1, 768) (matching the patch embedding dimensions), and this token is broadcasted across the batch.
- **Concatenation**: This class token is concatenated to the beginning of the sequence of patch embeddings, resulting in a tensor of shape (None, 65, 768), where 65 includes the 64 patches and 1 class token.

6. Transformer Encoder

- The combined embeddings (patches + class token) are fed into a series of **Transformer Encoder** layers.
- Each transformer encoder layer consists of:
    - **Layer Normalization** and **Multi-Head Self-Attention**: The self-attention mechanism allows each patch to interact with every other patch, capturing long-range dependencies and contextual relationships within the image.
    - **Skip Connection**: The output of self-attention is added to the input (skip connection), preserving the original information while adding the attention-

based output.

    - **Feed-Forward Network (MLP)**: Each transformer encoder block has a feed-forward network, or MLP, that further processes the data through dense layers and non-linear activations.
    - **Another Skip Connection**: The output from the MLP is added back to the input of the MLP, allowing the model to retain information from earlier layers.

- **Repeating Transformer Layers**: This process is repeated for num_layers times (12 in this case), where each layer refines the representation of each patch and the class token.

7. Final Processing for Classification

- **Layer Normalization**: After the transformer encoder layers, a final layer normalization is applied to stabilize the output.
- **Selecting the Class Token**: The model focuses on the output of the class token (i.e., x[:, 0, :]). Since the class token has been interacting with all patch embeddings throughout the transformer layers, it now contains a summary representation of the entire image.
- **Dense Layer for Classification**: The class token output is passed through a final Dense layer with softmax activation to produce probabilities for each class. The number of units in this layer matches the number of classes (2 in this case, for "benign" and "malignant").

8. Output

- The final output is a vector of probabilities, indicating the model's confidence in each class. The highest probability indicates the predicted class for the input image (either benign or malignant in this case).

Summary of Architecture

This architecture effectively combines:

- **ResNet-50 (CNN)** for extracting spatial features from the input image.
- **Vision Transformer (ViT)** for capturing long-range dependencies and global relationships across the patches.
- **Class Token** to aggregate information from all patches for final classification.

- **Multi-Head Attention** in the Transformer to allow each patch to attend to every other patch, enhancing contextual understanding.

This hybrid design leverages both CNN’s strengths in feature extraction and the Transformer’s capabilities in processing global relationships, making it well-suited for complex image classification tasks, such as melanoma detection.

Chapter 4

FINDINGS AND DISCUSSION

4.1 DISCUSSION

The data set used for this paper is the Skin Cancer MNIST: HAM10000 dataset, which contains high-resolution dermatoscopic images of different skin conditions and comprehensive metadata for each patient. The classification is made across seven different classes of skin lesions, including melanoma, basal cell carcinoma, and benign keratosis-like lesions. To ensure the quality and consistency of the data, extensive preprocessing steps were implemented. For the dermatoscopic images, preprocessing included resizing, normalization, and data augmentation techniques like rotation, flipping, and zooming, This improved the ability of the model to generalize over different types of lesions. Metadata, such as patient age, sex, and location of lesion, was standardized and encoded for compatibility with machine learning models. The heterogeneity and richness of this dataset provided a robust foundation for developing a deep-learning-based hybrid model that could effectively classify the different types of skin cancer.

4.2. Analysis of Data

The analysis phase focused on understanding the distribution and characteristics of the dataset to optimize model training. The dataset comprises over 10,000 dermatoscopic images, categorized into seven skin lesion types: Melanoma (MEL), Basal Cell Carcinoma (BCC), Benign Keratosis-like Lesions (BKL), Actinic Keratoses (AK), Dermatofibroma (DF), Melanocytic Nevi (NV), and Vascular Lesions (VASC). Initial data exploration revealed class imbalances, with Melanocytic Nevi (NV) being the most represented class and rarer conditions like Dermatofibroma (DF) underrepresented. This imbalance necessitated the use of techniques such as oversampling, undersampling, and class-weight adjustments during model training to prevent bias toward the more prevalent categories.

The metadata analysis highlighted the importance of patient demographics in skin cancer detection. For instance, melanoma was more frequently observed in older patients, suggesting age as a significant factor in the model’s predictive accuracy. The metadata, including patient age, sex, and anatomical site, was preprocessed by encoding categorical variables and normalizing numerical data to ensure uniformity across features. Data cleaning involved handling missing values through imputation and removing duplicate entries, which improved the overall quality of the dataset and enhanced the model’s predictive performance.

4.3 Experimental Setup

The experimental phase was conducted on **Google Colab**, leveraging its powerful GPU resources to accelerate the training of deep learning models. The use of Google Colab’s collaborative features allowed for efficient team collaboration, enabling multiple iterations and improvements in model development. The platform’s scalability was critical in handling the computational demands of training a hybrid model combining **Convolutional Neural Networks (CNNs)** and **Vision Transformers (ViTs)**. The model development pipeline was structured to utilize the benefits of CNNs in capturing local features and the strengths of Vision Transformers in identifying global patterns within dermatoscopic images.

For integration with a user-friendly diagnostic tool, **Visual Studio Code (VSCode)** was used for seamless development and testing of the machine learning model. The backend was developed to support real-time predictions, where users can upload dermatoscopic images via a web interface, and receive diagnostic feedback. VSCode’s debugging tools were essential for integrating the machine learning model with a frontend interface, ensuring smooth data flow from user input to model output.

4.4 Evaluation Metrics

The evaluation of the recommendation system relied on several performance metrics, which assessed the model's ability to correctly recommend doctors by using Equations (8) to (11)

$$Accuracy = \frac{Number\ of\ correct\ Predictions}{Total\ Predictions} \qquad (8)$$

$$Precision = \frac{TP}{TP+FP} \qquad (9)$$

$$Recall = \frac{TP}{TP+FN} \qquad (10)$$

$$F1\ Score = \frac{2\times Precision \times Recall}{Precision+Recall} \qquad (11)$$

Where TP is True Positives, FP is False Positives, and FN is False Negatives.

The use of these metrics allowed for a nuanced understanding of the model's strengths and areas for improvement, helping guide future refinements to enhance reliability in clinical use.

4.5 Insights

The hybrid deep learning model developed for skin cancer detection demonstrated significant success in accurately classifying various types of skin lesions using the **HAM10000 dataset**. The model, which integrates both **Convolutional Neural Networks (CNNs)** and **Vision Transformers (ViTs)**, achieved high accuracy, particularly in distinguishing between malignant and benign lesions. The CNN component effectively captured local features such as textures, edges, and color variations, while the ViT component leveraged self-attention mechanisms to understand the global context within the images. This combination proved to be particularly effective in detecting well-defined skin conditions, such as melanoma, basal cell carcinoma, and melanocytic nevi, which have distinct visual characteristics.

The model's performance was especially strong in diagnosing lesions with clear and identifiable patterns. For example, it showed high precision in detecting melanoma, a potentially deadly form of skin cancer, where early and accurate diagnosis is crucial for patient outcomes. The use of **data augmentation techniques**, such as rotation and flipping, improved the model’s ability to generalize across diverse image samples, resulting in robust performance across multiple lesion categories. Additionally, the integration of patient metadata, such as age and lesion location, further enhanced the model's predictive accuracy, making it a powerful tool for clinical decision support in dermatology.

However, the model faced challenges when dealing with skin lesions that have overlapping visual characteristics. For instance, benign keratosis-like lesions (BKL) and actinic keratoses (AK) share similar features, making it difficult for the model to accurately differentiate between them. This overlap in visual patterns led to occasional misclassifications, highlighting the limitations of the model in handling ambiguous cases. The confusion matrix analysis revealed that misclassifications were more frequent among classes with subtle differences, particularly in cases where the lesion appearance was atypical or influenced by factors such as lighting conditions and skin tone variations.

This would demand more refinement of the model to better address these challenges. For instance, it would involve feature improvement, where multi-scale feature learning and contextual embeddings may present a more refined view of complex lesion patterns. Moreover, transfer learning based on a pre-trained model within the domain may improve the recognition of rare or less common skin conditions by the system. Another approach could be using GANs, they generate some synthetic images to populate the data space and increase its diversity, making it easier to learn to discern between visually similar lesion types.

The inclusion of **Explainable AI (XAI)** techniques, such as **Grad-CAM (Gradient-weighted Class Activation Mapping)**, was instrumental in interpreting the model’s predictions. By generating heatmaps that highlight the areas of the image most influential in the decision-making process, the system provided dermatologists with greater transparency and confidence in the AI-driven diagnosis. This interpretability is essential in clinical settings, where trust in automated systems is critical for adoption.

Despite the model’s overall success, there are opportunities for enhancement in handling cases with high intra-class variability and inter-class similarity. Future work may include incorporating additional data sources, such as patient medical history and genetic factors, to improve the model’s diagnostic precision. Exploring advanced architectures like **Hybrid Transformers with Dynamic Convolutional Layers** could also enhance feature representation, leading to better differentiation between complex and overlapping lesion types.

Overall, the hybrid deep learning model presents a promising approach to improving skin cancer detection. Its ability to accurately classify common and well-defined lesions underscores its potential for integration into telemedicine platforms, where quick and reliable diagnosis can significantly improve patient outcomes. By addressing the current limitations and expanding the system’s capabilities, this AI-driven solution can provide a more comprehensive tool for early skin cancer detection, ultimately supporting dermatologists in delivering better patient care.

Chapter 5

RESULTS

5.1 Results from ResNet-50

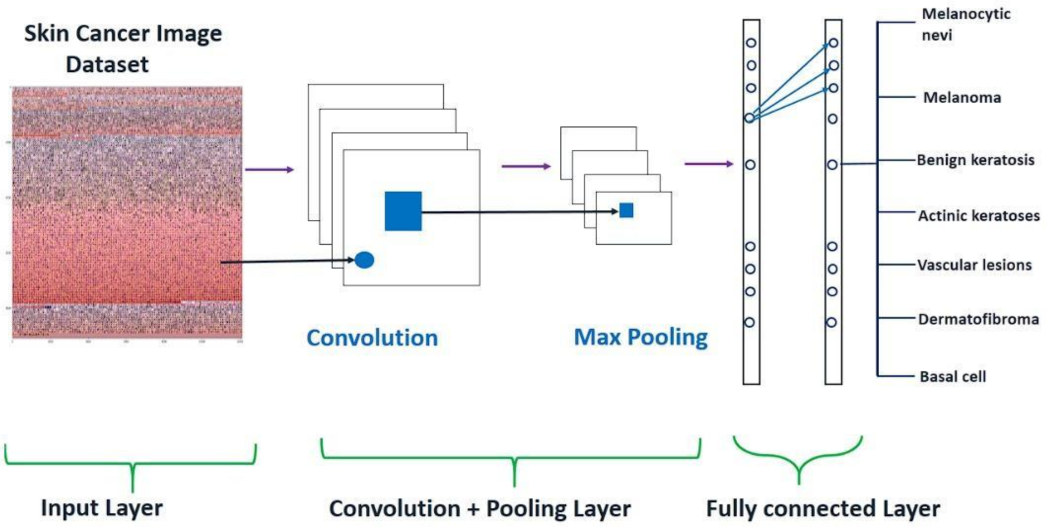


Fig 5. Pretrained ResNet-50

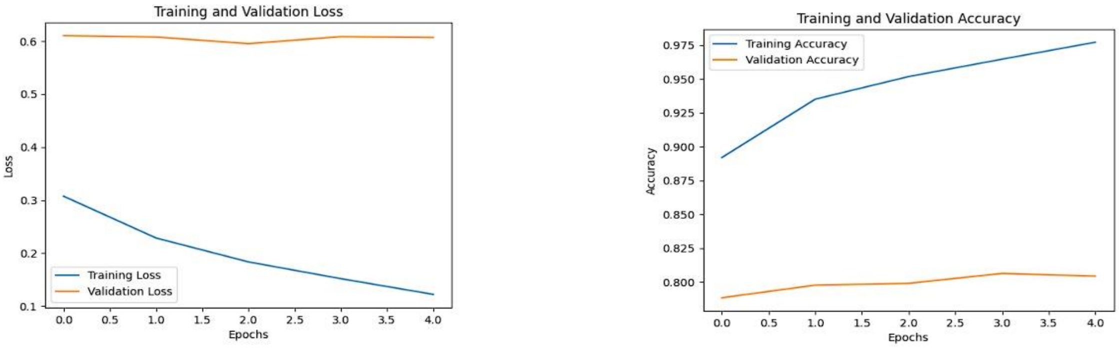


Fig 6. Training and Validation Results

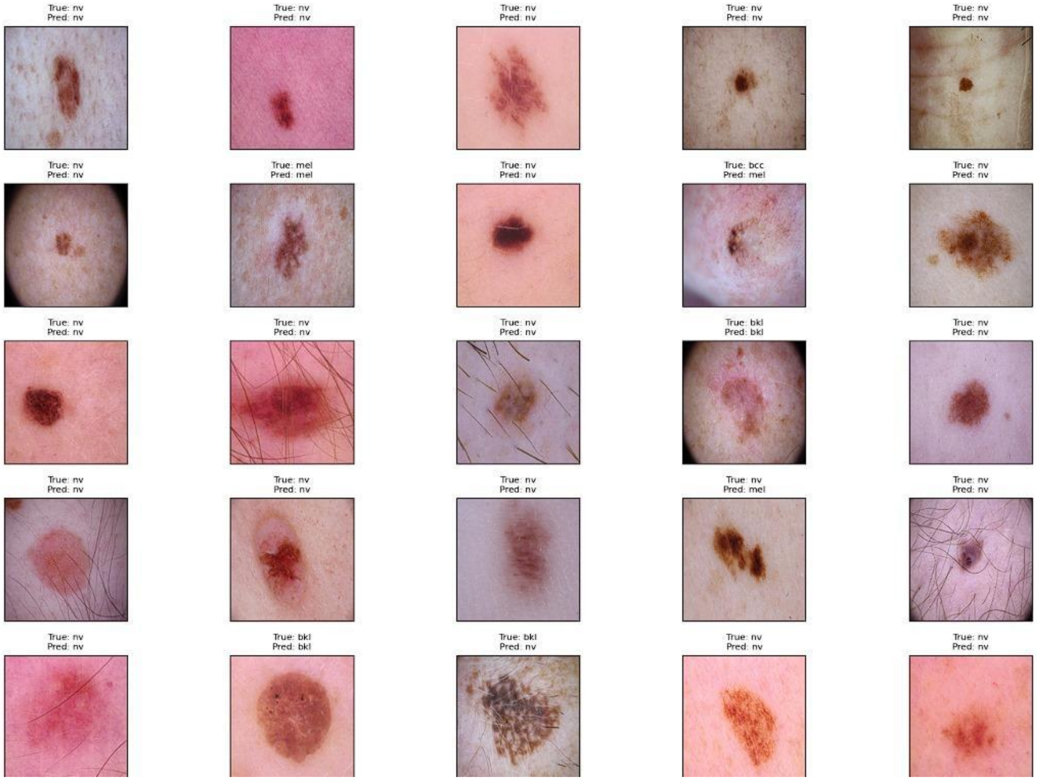


Fig 7. Results of pretrained ResNet-50

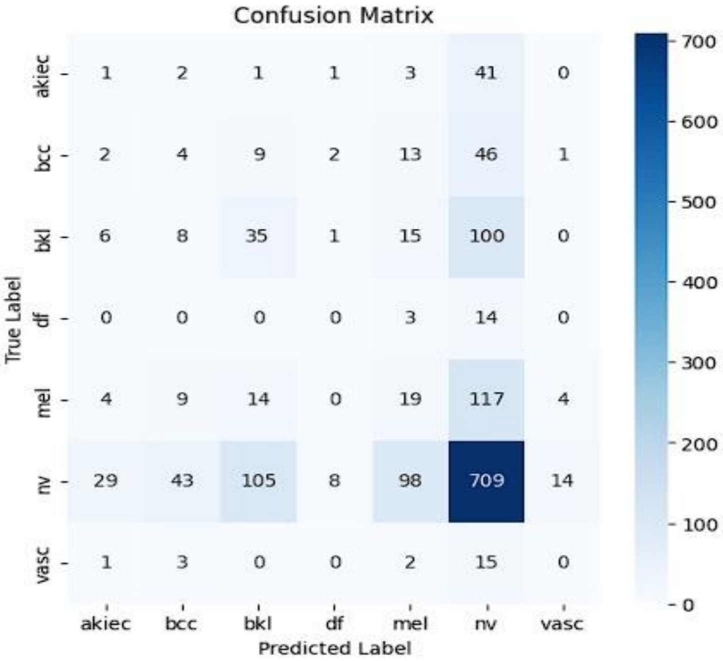
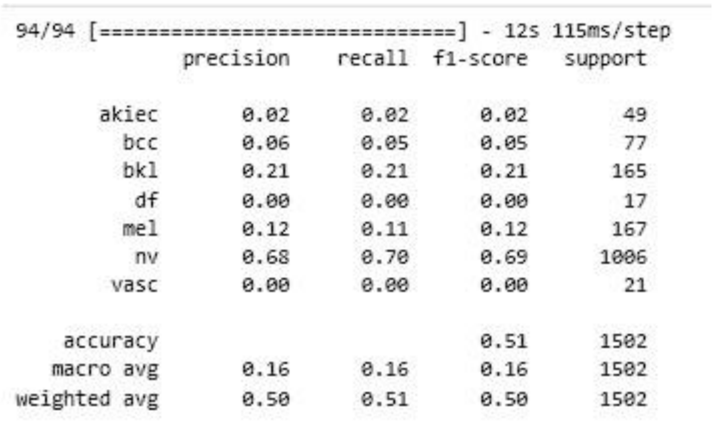


Fig 8. Confusion matrix of pretrained ResNet-50



```
94/94 [==============================] - 12s 115ms/step
              precision    recall  f1-score   support

       akiec       0.02      0.02      0.02        49
         bcc       0.06      0.05      0.05        77
         bkl       0.21      0.21      0.21       165
          df       0.00      0.00      0.00        17
         mel       0.12      0.11      0.12       167
          nv       0.68      0.70      0.69      1006
        vasc       0.00      0.00      0.00        21

    accuracy                           0.51      1502
   macro avg       0.16      0.16      0.16      1502
weighted avg       0.50      0.51      0.50      1502
```

Fig 9. Classification Report of pretrained ResNet-50

5.2 Results from ViT(Vision Transformer)

i) ViT B – 32

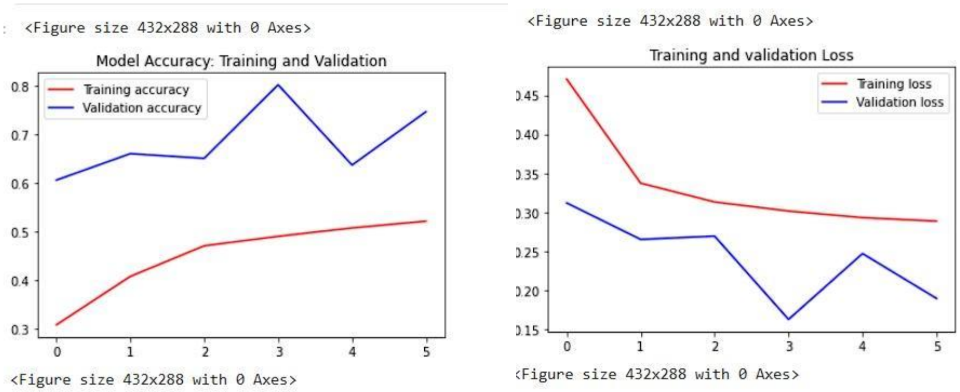


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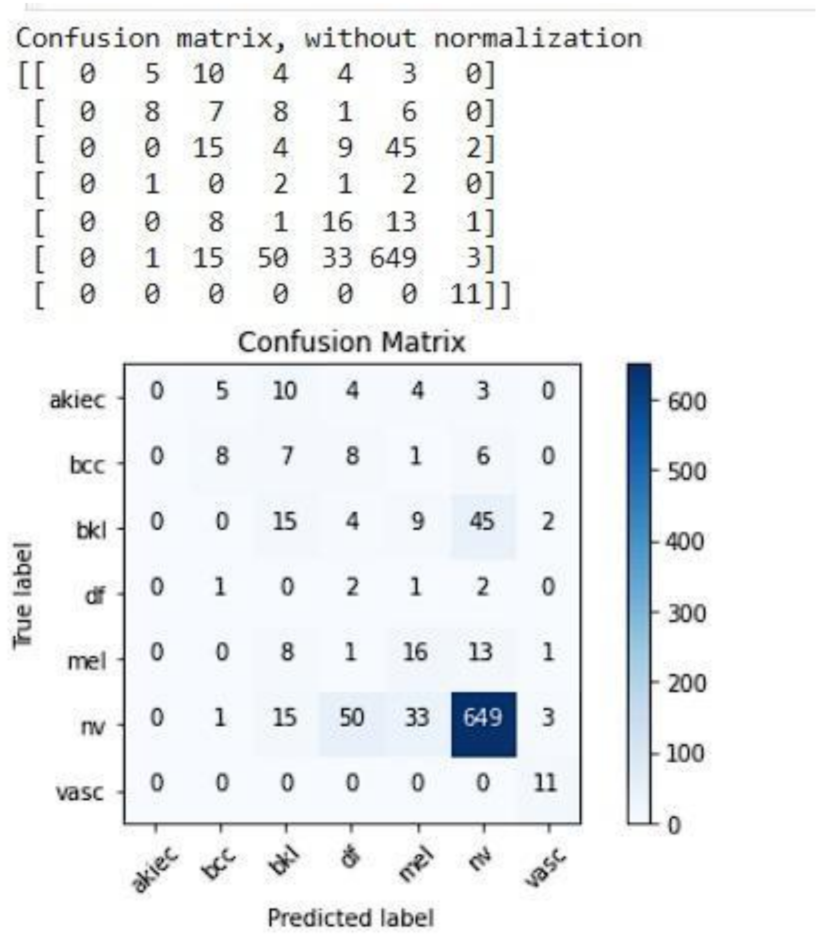
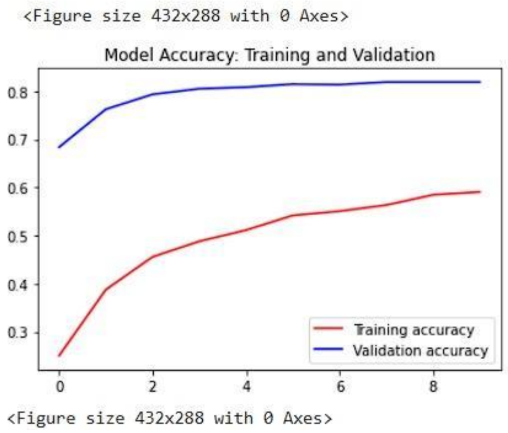
Fig 10. Training and Validation results of ViT B -32



```
Confusion matrix, without normalization
[[  0   5  10   4   4   3   0]
 [  0   8   7   8   1   6   0]
 [  0   0  15   4   9  45   2]
 [  0   1   0   2   1   2   0]
 [  0   0   8   1  16  13   1]
 [  0   1  15  50  33 649   3]
 [  0   0   0   0   0   0  11]]
```

Fig 11. Confusion matrix of ViT B -32

ii) ViT B – 16



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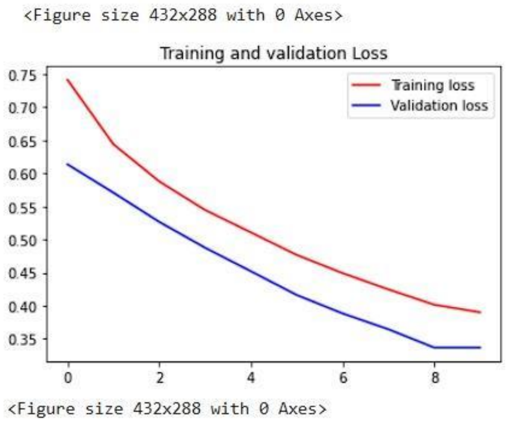

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<Figure size 432x288 with 0 Axes>
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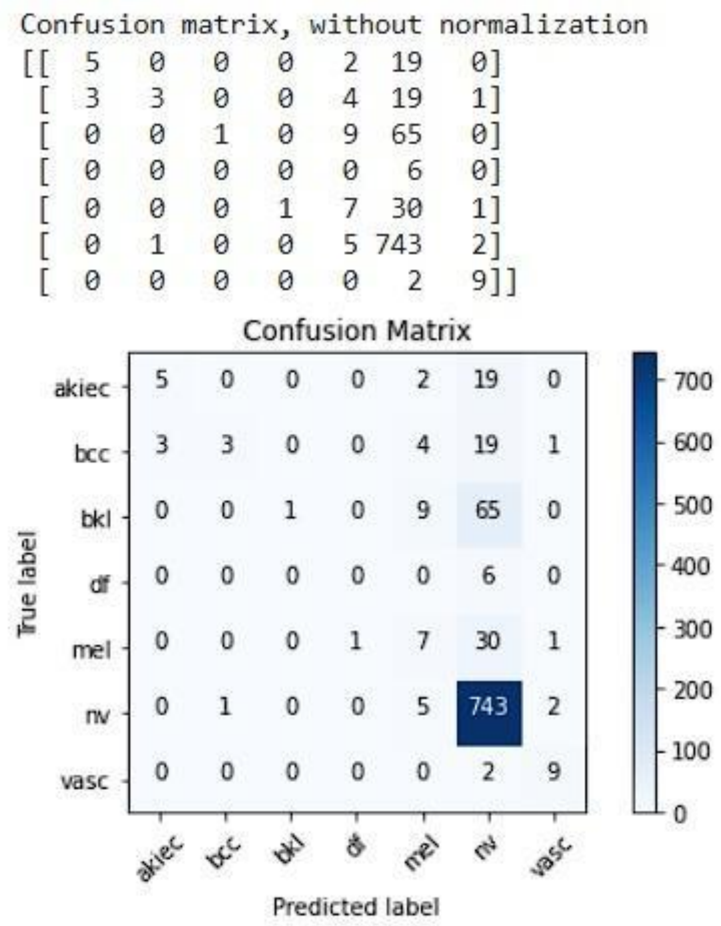
Fig 12. Training and Validation results of ViT B -16



```
Confusion matrix, without normalization
[[  5   0   0   0   2  19   0]
 [  3   3   0   0   4  19   1]
 [  0   0   1   0   9  65   0]
 [  0   0   0   0   0   6   0]
 [  0   0   0   1   7  30   1]
 [  0   1   0   0   5 743   2]
 [  0   0   0   0   0   2   9]]
```

Fig 13. Confusion Matrix of ViT B -16

Chapter 6

CONCLUSION

6.1 CONCLUSION

This project focused on developing a robust deep learning-based solution for early skin cancer detection, leveraging advanced neural network architectures to improve diagnostic accuracy. The study demonstrated the effectiveness of **Vision Transformers (ViTs)** over traditional **Convolutional Neural Networks (CNNs)** in the domain of medical image processing. Unlike CNNs, which primarily excel at capturing local patterns, Vision Transformers leverage self-attention mechanisms to capture both local and global features, making them particularly suitable for complex medical images like dermatoscopic scans. This ability to understand long-range dependencies within images allowed the ViT models to achieve superior classification performance, particularly in classifying between benign and malignant skin lesions.

Among the Vision Transformer variants tested, **ViT-B/16** outperformed **ViT-B/32**, highlighting the impact of patch size on model accuracy. The smaller patch size in ViT-B/16 enabled the model to capture finer details in dermatoscopic images, leading to more precise feature extraction and improved diagnostic accuracy. This was especially important in detecting subtle differences between visually similar lesions, such as benign keratosis and melanoma, which are critical for early and accurate diagnosis. The results confirm that Vision Transformers, particularly ViT-B/16, offer a significant advantage in skin cancer detection tasks by providing higher sensitivity and specificity compared to traditional CNN models.

The importance of early and accurate skin cancer detection cannot be overstated. Skin cancer, particularly melanoma, is one of the most aggressive and potentially fatal forms of cancer if not diagnosed and treated early. This project aimed to address this challenge by leveraging state-of-the-art AI models to assist dermatologists in making timely and accurate diagnoses, thereby improving patient outcomes. The superior performance of Vision Transformers in this study not only demonstrates their potential in the medical imaging field but also paves the way for their integration into clinical decision support systems. By enhancing the accuracy of automated skin cancer screening, this technology can play a crucial role in reducing the mortality rates associated with skin cancer and expanding access to high-quality dermatological care, especially in regions with limited medical resources.

In conclusion, the combination of deep learning and Vision Transformers, especially ViT-B/16, holds great promise for enhancing the accuracy and reliability of the classification of skin cancer. This could end up turning AI around in a type of transformation within the health care sector—ensuring faster and more accurate diagnosis that can lead to better healthcare outcomes. There can be further optimization of ViT models, incorporating multimodal data to further enhance the strength of diagnosis by the system.

6.2 SCOPE FOR IMPROVEMENT

Scope for Improvement

While the current hybrid deep learning model for skin cancer detection has shown promising results in accurately classifying skin lesions, there are several areas where the system can be further enhanced to improve its performance, efficiency, and scalability. These enhancements can significantly increase the model's utility in real-world clinical settings and telemedicine platforms. Below are some key areas identified for potential improvements:

1. **Custom Evaluation Metrics**:

   Current model evaluation relies mainly on standard metrics, which include accuracy, precision, recall, and F1-score. However, a clinical setting requires a better understanding of the type of sensitivity of skin cancer detection, specifically the ability to identify malignant lesions such as melanoma. Introducing **custom evaluation metrics** such as the **Mean Sensitivity Index (MSI)**, **Specificity for High-Risk Categories**, and **False Negative Rate (FNR)** for critical conditions can provide a more nuanced assessment of the model's diagnostic capabilities. These tailored metrics would ensure that the model prioritizes minimizing false negatives in high-risk cases, thereby enhancing patient safety.

2. **Reduced Computational Resource Requirements**:

   The current hybrid architecture, which combines Convolutional Neural Networks

(CNNs) and Vision Transformers (ViTs), is computationally intensive, requiring high-end GPU resources for efficient training and inference. To make the model more accessible and deployable in resource-constrained environments, such as rural healthcare facilities or mobile devices, optimizations can be implemented. **Model pruning**, **quantization**, and the use of **lightweight architectures** like **MobileNet** or **EfficientNet-Lite** can significantly reduce the computational overhead without compromising accuracy. These adjustments will make the model more adaptable for real-time applications in telemedicine.

3. **Advanced Data Augmentation Techniques**:
   Although basic data augmentation techniques like rotation, flipping, and zooming are currently employed, there is scope to incorporate more sophisticated augmentation strategies to improve the model's robustness. **CutMix**, **MixUp**, and **Random Erasing** are advanced techniques that can generate more diverse training samples, helping the model to generalize better to unseen data. Additionally, **style transfer augmentation** can simulate variations in skin tones, lighting conditions, and imaging devices, thus addressing biases and improving the model's performance across different demographic groups

4. **Enhanced Interpretability with Explainable AI**:
   While the use of **Grad-CAM** and **Saliency Maps** has added a layer of interpretability, further improvements can be made to increase clinician trust. Integrating **Local Interpretable Model-agnostic Explanations (LIME)**, **SHAP (SHapley Additive exPlanations)**, or **Counterfactual Explanations** can provide deeper insights into the model's decision-making process. This would not only improve transparency but also assist dermatologists in validating the AI-generated diagnoses, ultimately leading to better adoption in clinical practice.

5. **Continuous Learning and Model Adaptation**:

   Skin cancer detection is an evolving field, with new types of lesions and variations being discovered. Implementing a **continuous learning framework** where the model can be periodically updated with new data can ensure that it remains accurate over time. Techniques like **Incremental Learning** and **Online Learning** can be employed to adapt the model to new lesion types without requiring a complete retraining, thereby saving computational resources.

Chapter 7

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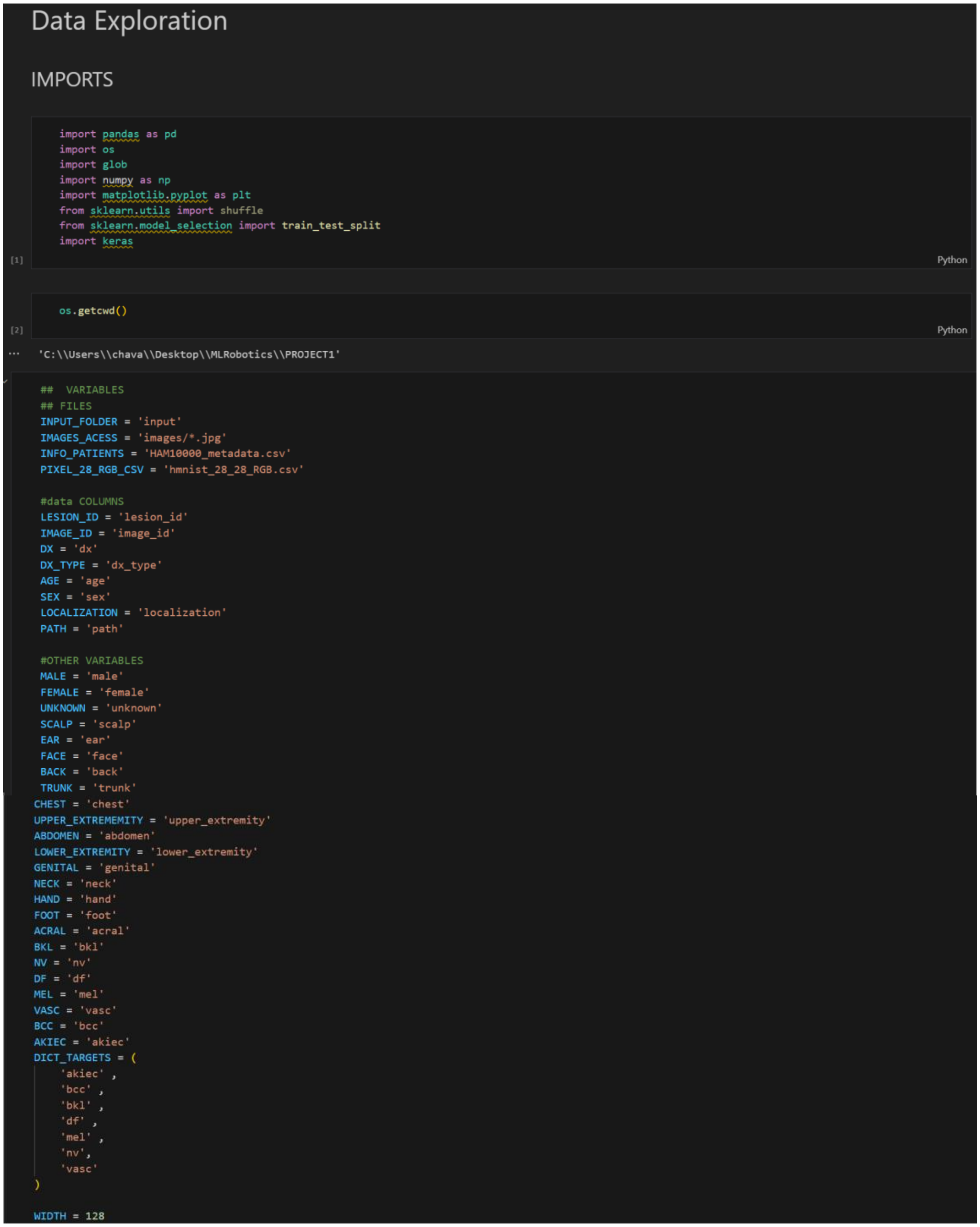
APPENDIX A – Sample Code



Data Exploration

IMPORTS

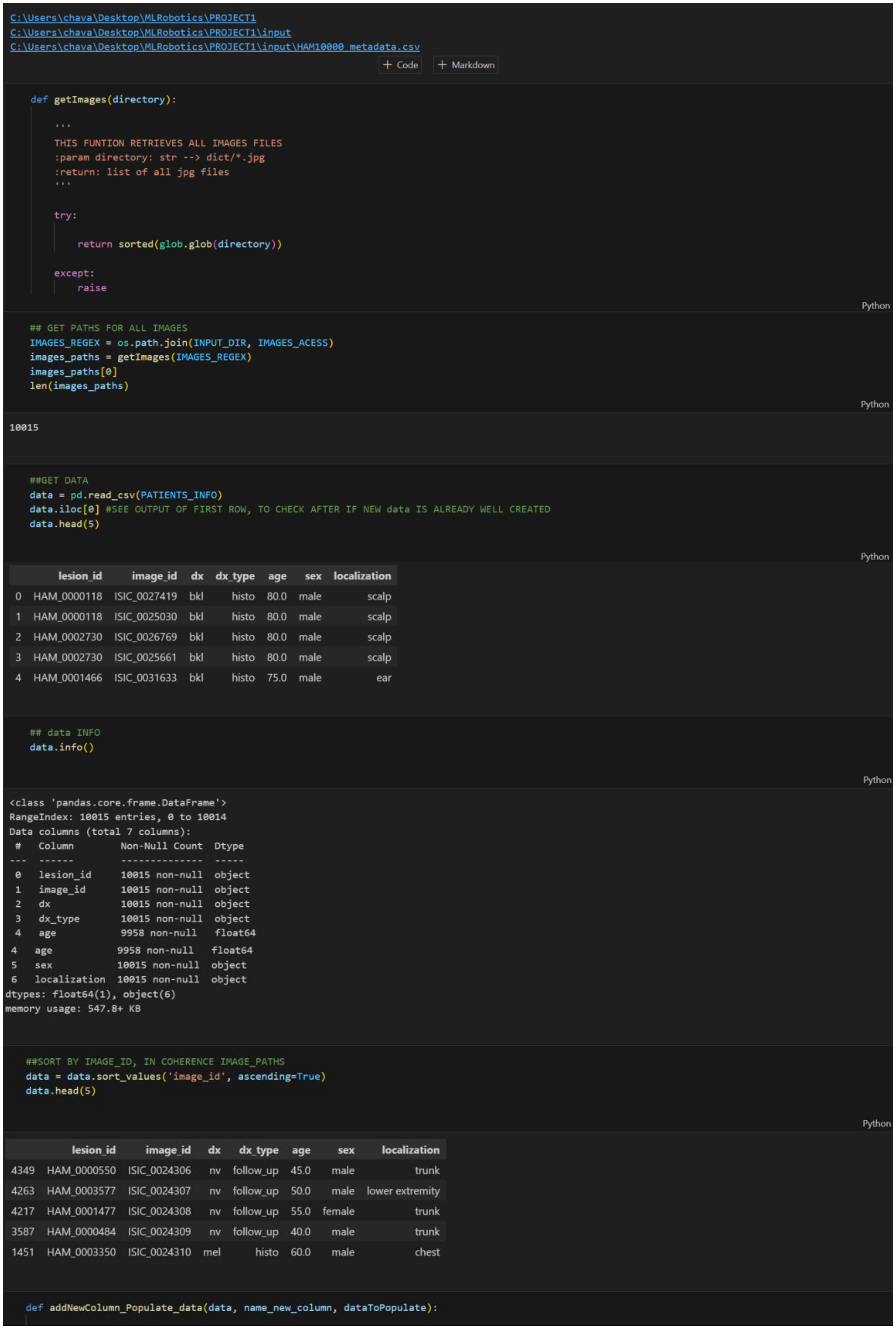
```python
import pandas as pd
import os
import glob
import numpy as np
import matplotlib.pyplot as plt
from sklearn.utils import shuffle
from sklearn.model_selection import train_test_split
import keras
```

```python
os.getcwd()
```

```
'C:\\Users\\chava\\Desktop\\MLRobotics\\PROJECT1'
```

```python
##  VARIABLES
## FILES
INPUT_FOLDER = 'input'
IMAGES_ACESS = 'images/*.jpg'
INFO_PATIENTS = 'HAM10000_metadata.csv'
PIXEL_28_RGB_CSV = 'hmnist_28_28_RGB.csv'

#data COLUMNS
LESION_ID = 'lesion_id'
IMAGE_ID = 'image_id'
DX = 'dx'
DX_TYPE = 'dx_type'
AGE = 'age'
SEX = 'sex'
LOCALIZATION = 'localization'
PATH = 'path'

#OTHER VARIABLES
MALE = 'male'
FEMALE = 'female'
UNKNOWN = 'unknown'
SCALP = 'scalp'
EAR = 'ear'
FACE = 'face'
BACK = 'back'
TRUNK = 'trunk'
CHEST = 'chest'
UPPER_EXTREMEMITY = 'upper_extremity'
ABDOMEN = 'abdomen'
LOWER_EXTREMITY = 'lower_extremity'
GENITAL = 'genital'
NECK = 'neck'
HAND = 'hand'
FOOT = 'foot'
ACRAL = 'acral'
BKL = 'bkl'
NV = 'nv'
DF = 'df'
MEL = 'mel'
VASC = 'vasc'
BCC = 'bcc'
AKIEC = 'akiec'
DICT_TARGETS = (
    'akiec' ,
    'bcc' ,
    'bkl' ,
    'df' ,
    'mel' ,
    'nv',
    'vasc'
)

WIDTH = 128
```

Appendix 1.1 Imports and Required Variables



```
C:\Users\chava\Desktop\MLRobotics\PROJECT1
C:\Users\chava\Desktop\MLRobotics\PROJECT1\input
C:\Users\chava\Desktop\MLRobotics\PROJECT1\input\HAM10000_metadata.csv
```

```python
def getImages(directory):

    '''
    THIS FUNTION RETRIEVES ALL IMAGES FILES
    :param directory: str --> dict/*.jpg
    :return: list of all jpg files
    '''

    try:

        return sorted(glob.glob(directory))

    except:
        raise
```

```python
## GET PATHS FOR ALL IMAGES
IMAGES_REGEX = os.path.join(INPUT_DIR, IMAGES_ACESS)
images_paths = getImages(IMAGES_REGEX)
images_paths[0]
len(images_paths)
```

```
10015
```

```python
##GET DATA
data = pd.read_csv(PATIENTS_INFO)
data.iloc[0] #SEE OUTPUT OF FIRST ROW, TO CHECK AFTER IF NEW data IS ALREADY WELL CREATED
data.head(5)
```

	lesion_id	image_id	dx	dx_type	age	sex	localization
0	HAM_0000118	ISIC_0027419	bkl	histo	80.0	male	scalp
1	HAM_0000118	ISIC_0025030	bkl	histo	80.0	male	scalp
2	HAM_0002730	ISIC_0026769	bkl	histo	80.0	male	scalp
3	HAM_0002730	ISIC_0025661	bkl	histo	80.0	male	scalp
4	HAM_0001466	ISIC_0031633	bkl	histo	75.0	male	ear

```python
## data INFO
data.info()
```

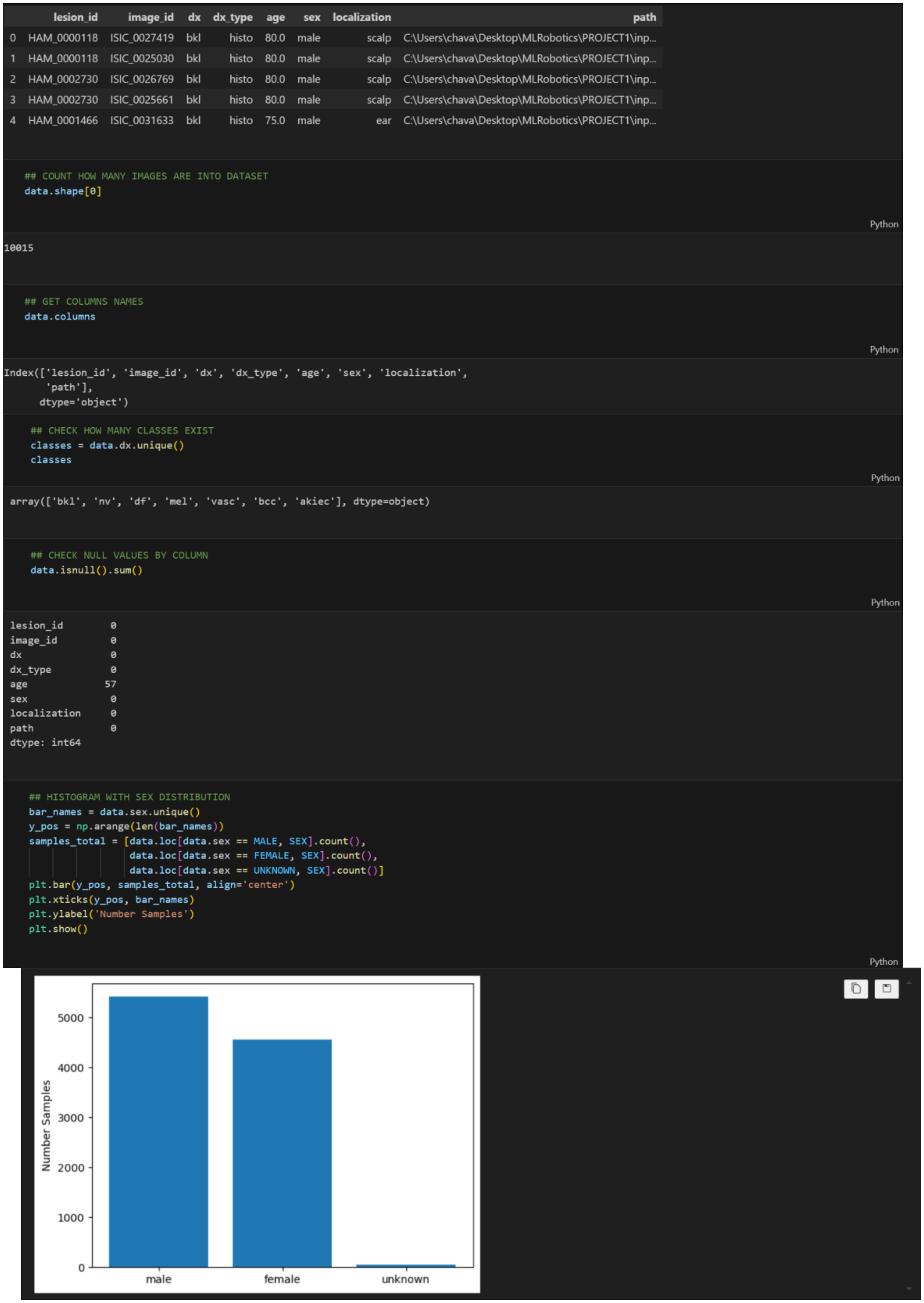
```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 10015 entries, 0 to 10014
Data columns (total 7 columns):
 #   Column        Non-Null Count  Dtype
---  ------        --------------  -----
 0   lesion_id     10015 non-null  object
 1   image_id      10015 non-null  object
 2   dx            10015 non-null  object
 3   dx_type       10015 non-null  object
 4   age           9958 non-null   float64
 4   age           9958 non-null   float64
 5   sex           10015 non-null  object
 6   localization  10015 non-null  object
dtypes: float64(1), object(6)
memory usage: 547.8+ KB
```

```python
##SORT BY IMAGE_ID, IN COHERENCE IMAGE_PATHS
data = data.sort_values('image_id', ascending=True)
data.head(5)
```

	lesion_id	image_id	dx	dx_type	age	sex	localization
4349	HAM_0000550	ISIC_0024306	nv	follow_up	45.0	male	trunk
4263	HAM_0003577	ISIC_0024307	nv	follow_up	50.0	male	lower extremity
4217	HAM_0001477	ISIC_0024308	nv	follow_up	55.0	female	trunk
3587	HAM_0000484	ISIC_0024309	nv	follow_up	40.0	male	trunk
1451	HAM_0003350	ISIC_0024310	mel	histo	60.0	male	chest

```python
def addNewColumn_Populate_data(data, name_new_column, dataToPopulate):
```

Appendix 1.2 Importing Dataset



	lesion_id	image_id	dx	dx_type	age	sex	localization	path
0	HAM_0000118	ISIC_0027419	bkl	histo	80.0	male	scalp	C:\Users\chava\Desktop\MLRobotics\PROJECT1\inp...
1	HAM_0000118	ISIC_0025030	bkl	histo	80.0	male	scalp	C:\Users\chava\Desktop\MLRobotics\PROJECT1\inp...
2	HAM_0002730	ISIC_0026769	bkl	histo	80.0	male	scalp	C:\Users\chava\Desktop\MLRobotics\PROJECT1\inp...
3	HAM_0002730	ISIC_0025661	bkl	histo	80.0	male	scalp	C:\Users\chava\Desktop\MLRobotics\PROJECT1\inp...
4	HAM_0001466	ISIC_0031633	bkl	histo	75.0	male	ear	C:\Users\chava\Desktop\MLRobotics\PROJECT1\inp...

```
## COUNT HOW MANY IMAGES ARE INTO DATASET
data.shape[0]
```

Python

```
10015
```

```
## GET COLUMNS NAMES
data.columns
```

Python

```
Index(['lesion_id', 'image_id', 'dx', 'dx_type', 'age', 'sex', 'localization',
       'path'],
      dtype='object')
```

```
## CHECK HOW MANY CLASSES EXIST
classes = data.dx.unique()
classes
```

Python

```
array(['bkl', 'nv', 'df', 'mel', 'vasc', 'bcc', 'akiec'], dtype=object)
```

```
## CHECK NULL VALUES BY COLUMN
data.isnull().sum()
```

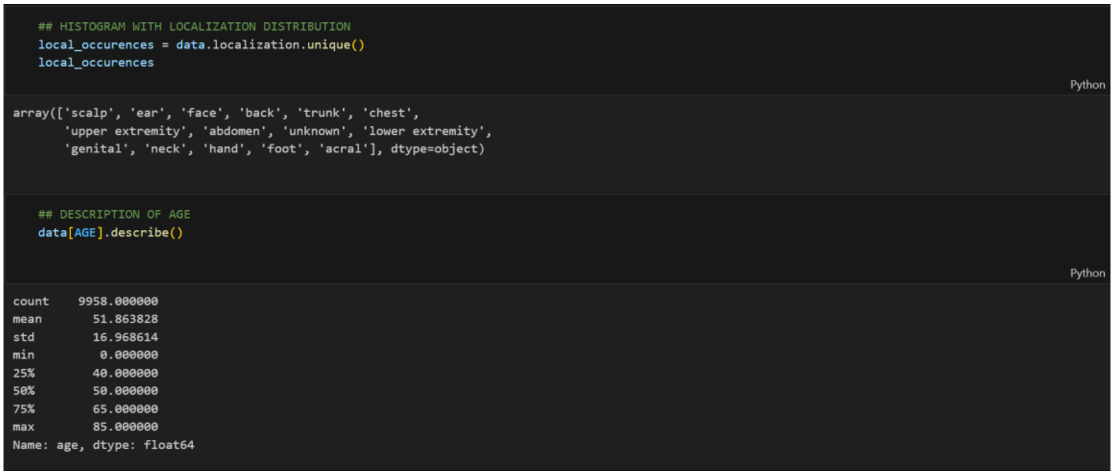
Python

```
lesion_id        0
image_id         0
dx               0
dx_type          0
age             57
sex              0
localization     0
path             0
dtype: int64
```

```
## HISTOGRAM WITH SEX DISTRIBUTION
bar_names = data.sex.unique()
y_pos = np.arange(len(bar_names))
samples_total = [data.loc[data.sex == MALE, SEX].count(),
                 data.loc[data.sex == FEMALE, SEX].count(),
                 data.loc[data.sex == UNKNOWN, SEX].count()]
plt.bar(y_pos, samples_total, align='center')
plt.xticks(y_pos, bar_names)
plt.ylabel('Number Samples')
plt.show()
```

Python

Appendix 1.3 Importing Dataset

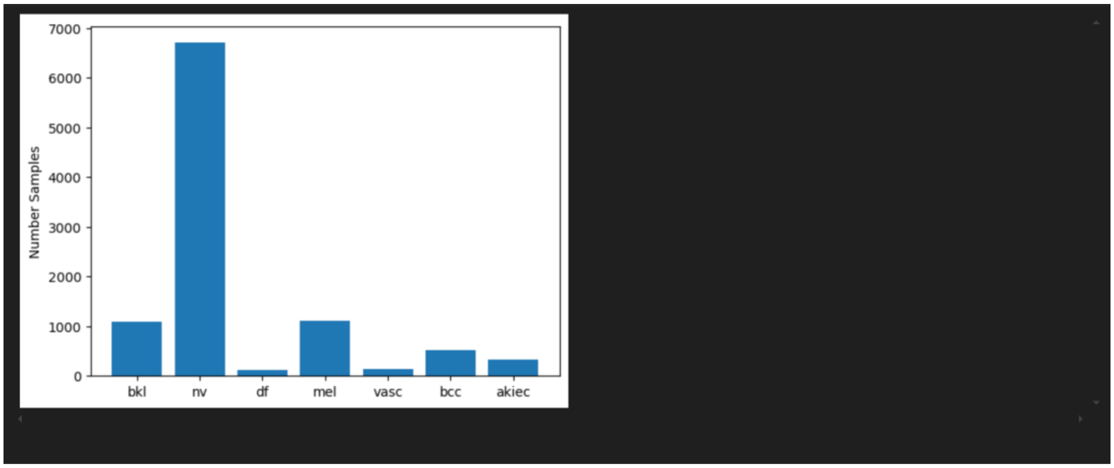


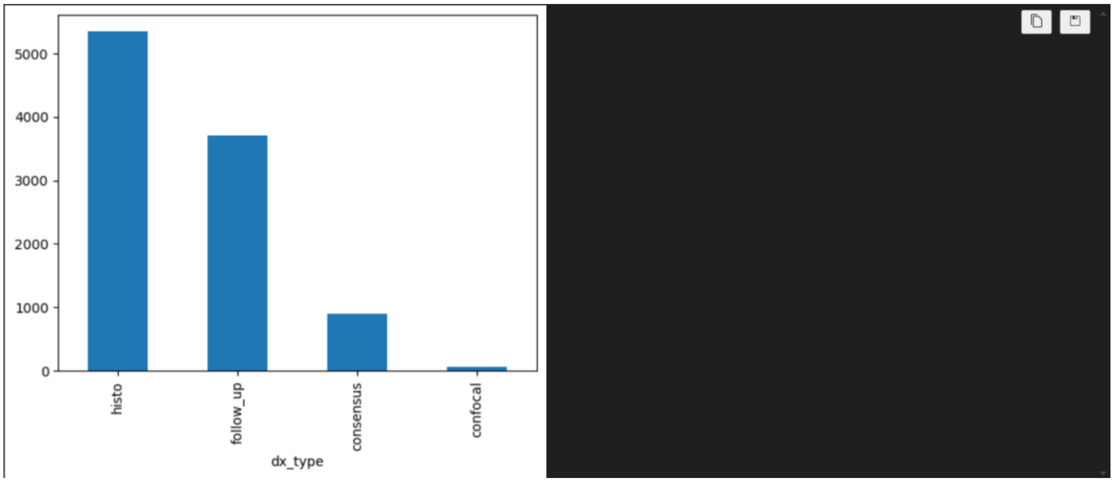
```
## HISTOGRAM WITH LOCALIZATION DISTRIBUTION
local_occurences = data.localization.unique()
local_occurences
```

```
array(['scalp', 'ear', 'face', 'back', 'trunk', 'chest',
       'upper extremity', 'abdomen', 'unknown', 'lower extremity',
       'genital', 'neck', 'hand', 'foot', 'acral'], dtype=object)
```

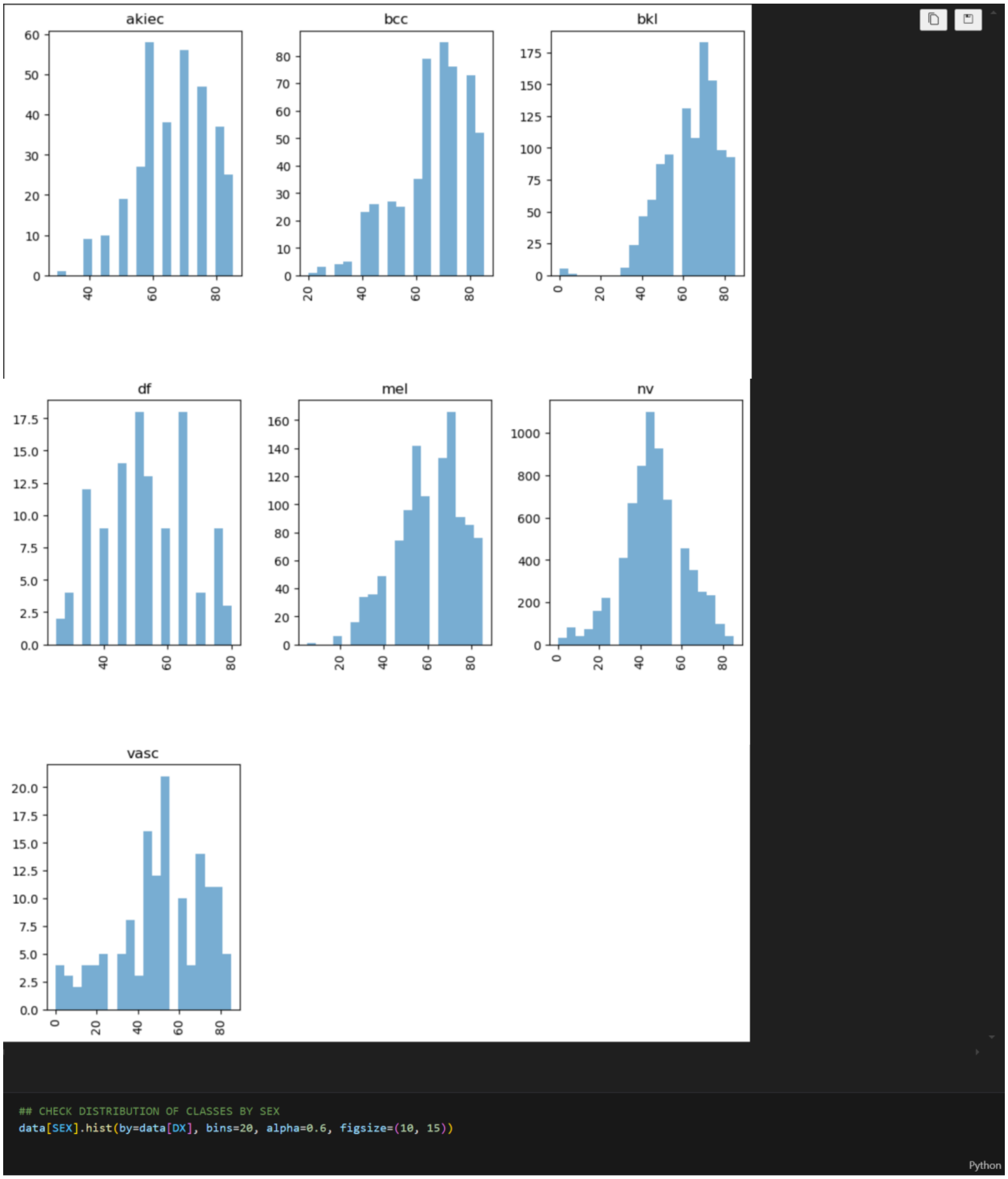
```
## DESCRIPTION OF AGE
data[AGE].describe()
```

```
count    9958.000000
mean       51.863828
std        16.968614
min         0.000000
25%        40.000000
50%        50.000000
75%        65.000000
max        85.000000
Name: age, dtype: float64
```



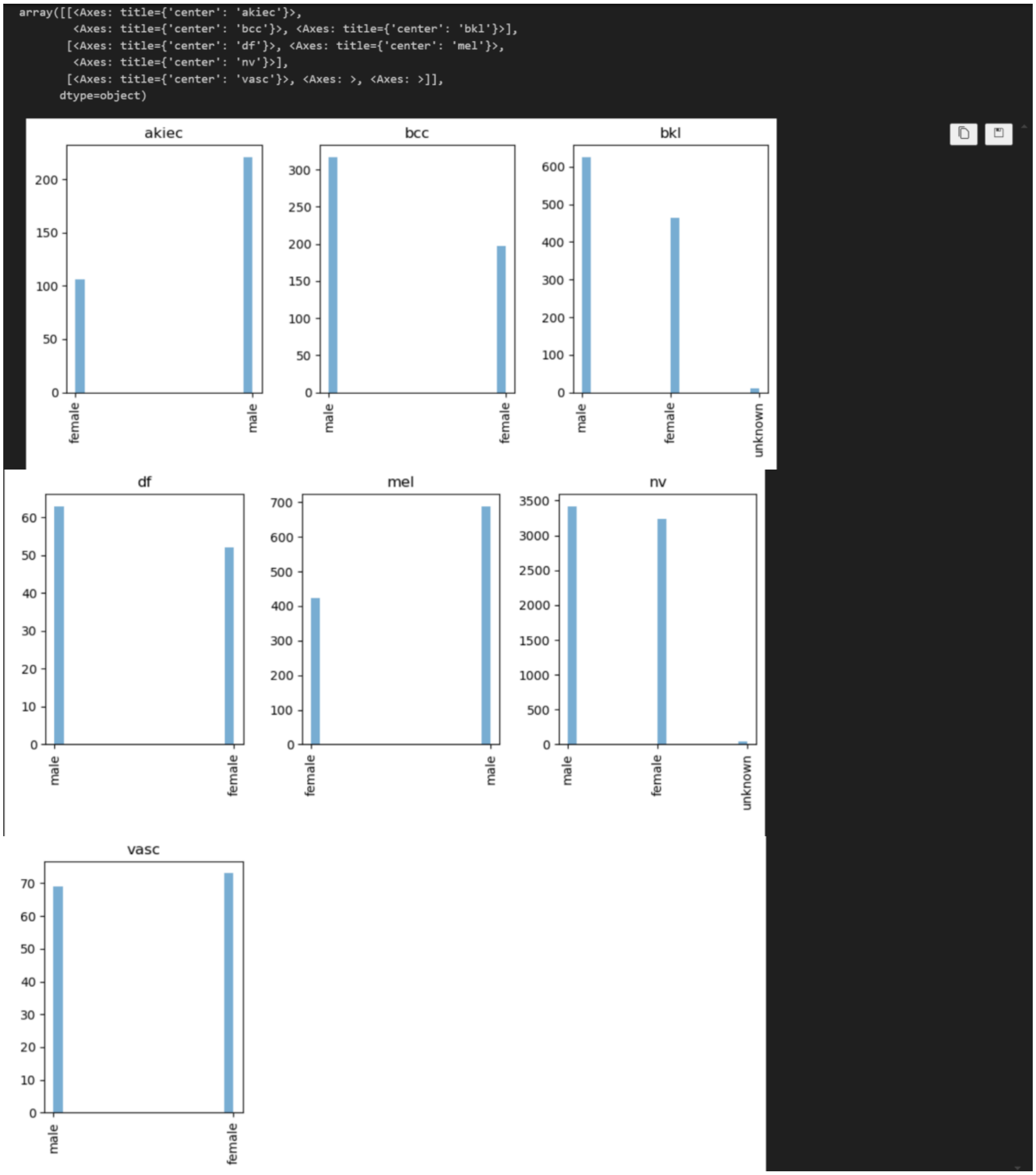


Appendix 1.4 Data Exploration



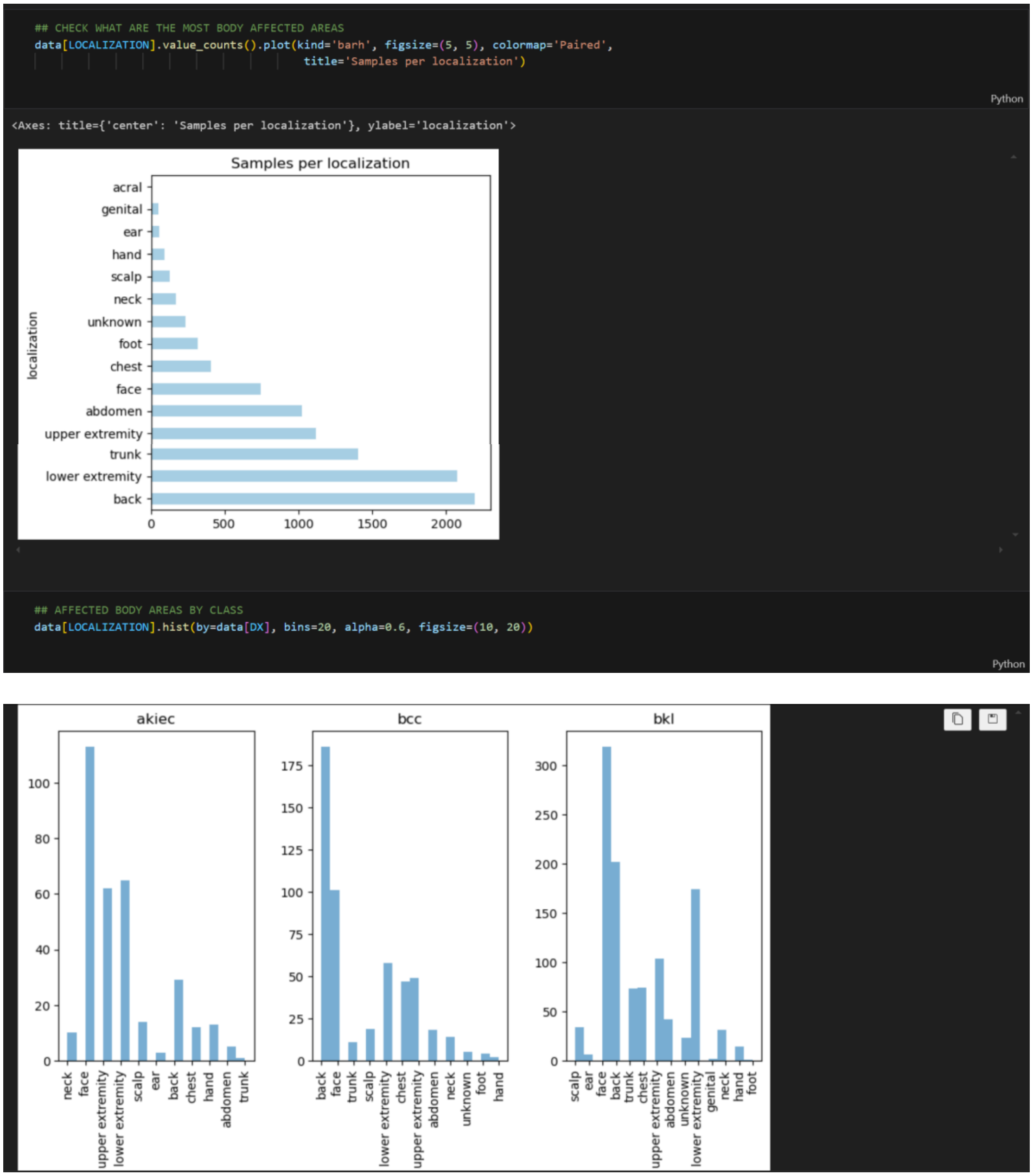
```
## CHECK DISTRIBUTION OF CLASSES BY SEX
data[SEX].hist(by=data[DX], bins=20, alpha=0.6, figsize=(10, 15))
```

Appendix 1.5 Data Exploration



```
array([[<Axes: title={'center': 'akiec'}>,
        <Axes: title={'center': 'bcc'}>, <Axes: title={'center': 'bkl'}>],
       [<Axes: title={'center': 'df'}>, <Axes: title={'center': 'mel'}>,
        <Axes: title={'center': 'nv'}>],
       [<Axes: title={'center': 'vasc'}>, <Axes: >, <Axes: >]],
      dtype=object)
```

Appendix 1.6 Data Exploration

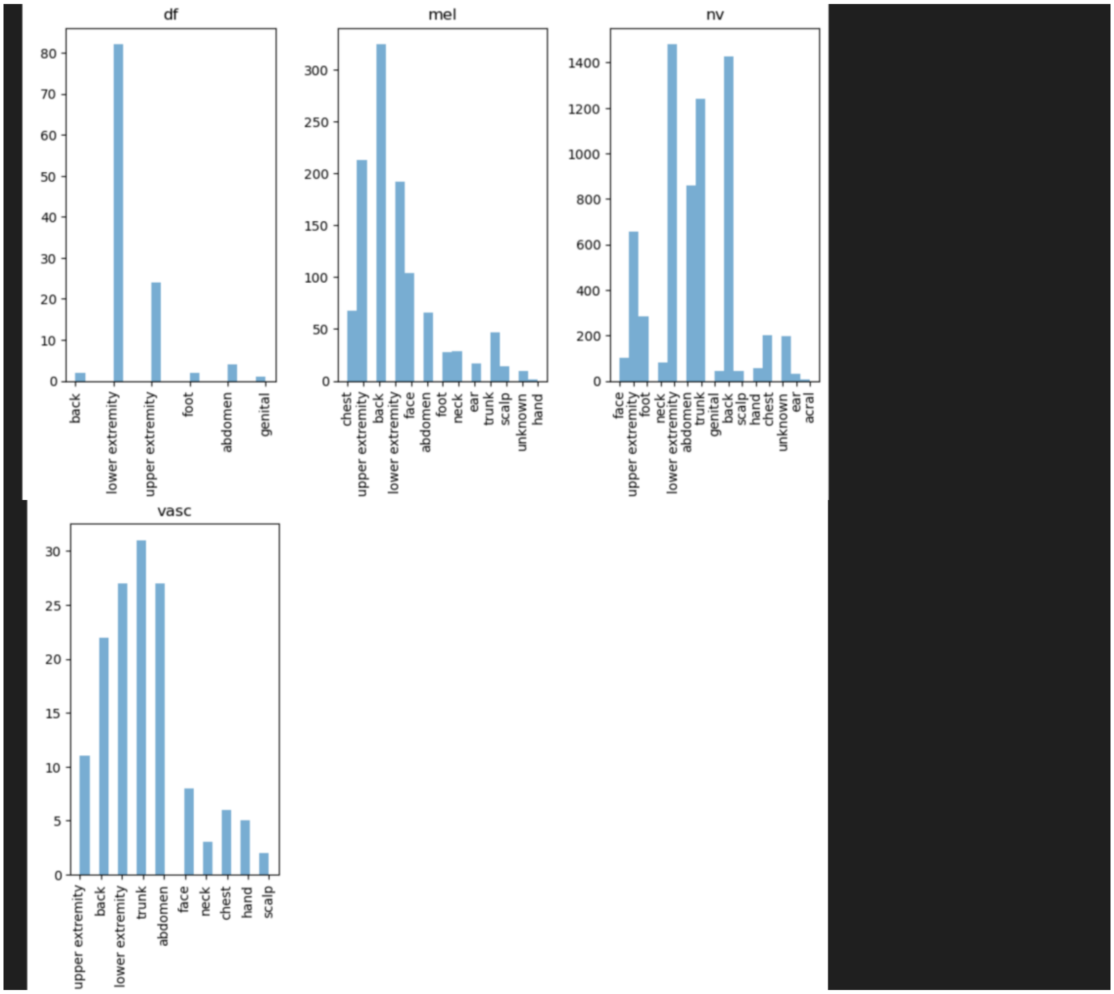


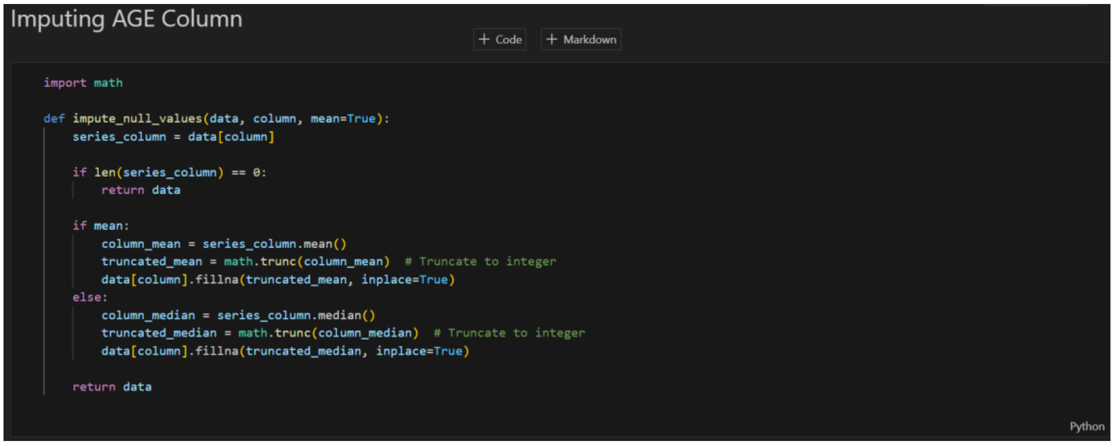
```python
## CHECK WHAT ARE THE MOST BODY AFFECTED AREAS
data[LOCALIZATION].value_counts().plot(kind='barh', figsize=(5, 5), colormap='Paired',
                                        title='Samples per localization')
```

```
<Axes: title={'center': 'Samples per localization'}, ylabel='localization'>
```

```python
## AFFECTED BODY AREAS BY CLASS
data[LOCALIZATION].hist(by=data[DX], bins=20, alpha=0.6, figsize=(10, 20))
```

Appendix 1.7 Data Exploration

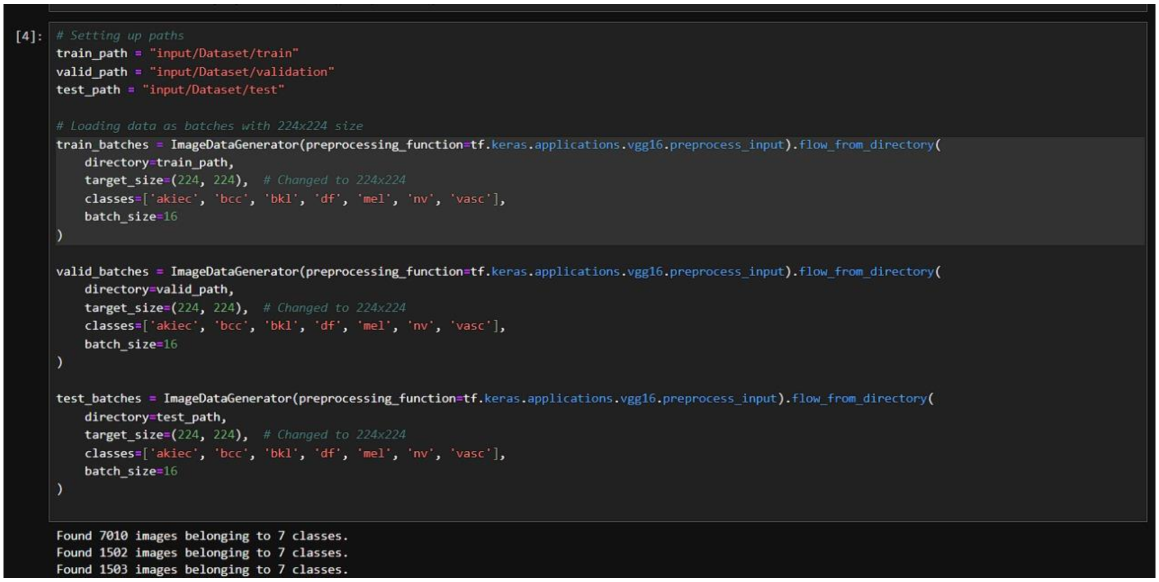




Imputing AGE Column

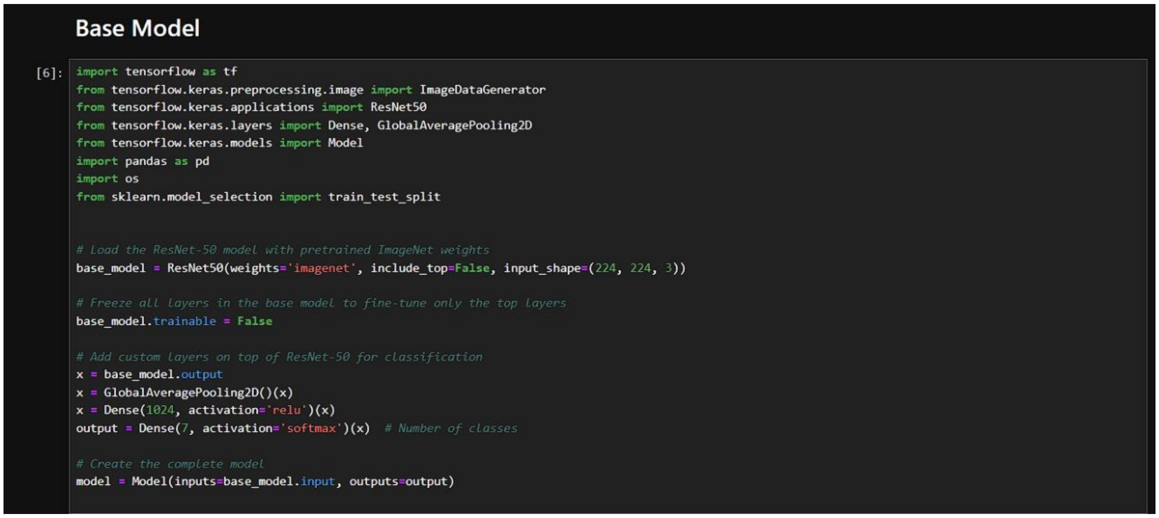
```python
import math

def impute_null_values(data, column, mean=True):
    series_column = data[column]

    if len(series_column) == 0:
        return data

    if mean:
        column_mean = series_column.mean()
        truncated_mean = math.trunc(column_mean)  # Truncate to integer
        data[column].fillna(truncated_mean, inplace=True)
    else:
        column_median = series_column.median()
        truncated_median = math.trunc(column_median)  # Truncate to integer
        data[column].fillna(truncated_median, inplace=True)

    return data
```

Appendix 1.7 Data Exploration



```
[4]: # Setting up paths
train_path = "input/Dataset/train"
valid_path = "input/Dataset/validation"
test_path = "input/Dataset/test"

# Loading data as batches with 224x224 size
train_batches = ImageDataGenerator(preprocessing_function=tf.keras.applications.vgg16.preprocess_input).flow_from_directory(
    directory=train_path,
    target_size=(224, 224),  # Changed to 224x224
    classes=['akiec', 'bcc', 'bkl', 'df', 'mel', 'nv', 'vasc'],
    batch_size=16
)

valid_batches = ImageDataGenerator(preprocessing_function=tf.keras.applications.vgg16.preprocess_input).flow_from_directory(
    directory=valid_path,
    target_size=(224, 224),  # Changed to 224x224
    classes=['akiec', 'bcc', 'bkl', 'df', 'mel', 'nv', 'vasc'],
    batch_size=16
)

test_batches = ImageDataGenerator(preprocessing_function=tf.keras.applications.vgg16.preprocess_input).flow_from_directory(
    directory=test_path,
    target_size=(224, 224),  # Changed to 224x224
    classes=['akiec', 'bcc', 'bkl', 'df', 'mel', 'nv', 'vasc'],
    batch_size=16
)

Found 7010 images belonging to 7 classes.
Found 1502 images belonging to 7 classes.
Found 1503 images belonging to 7 classes.
```

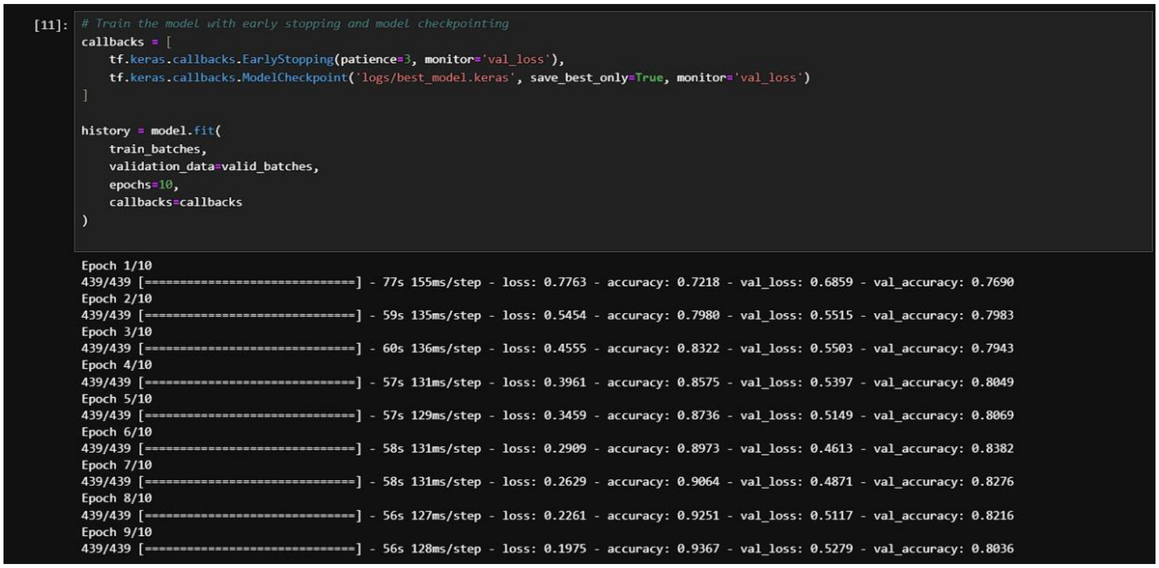
Appendix 2.1 Dividing the data into batches



Base Model

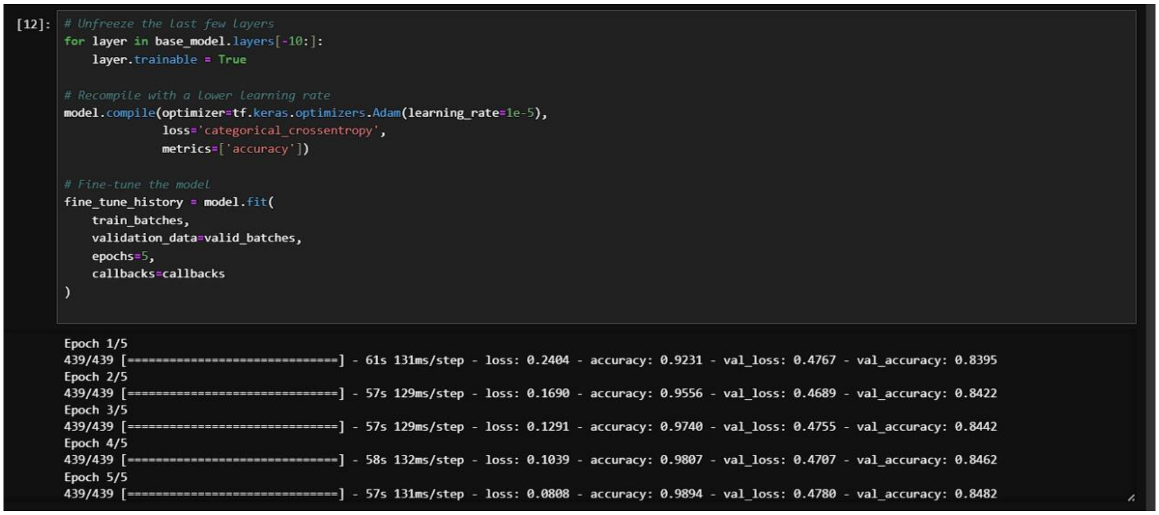
```
[6]: import tensorflow as tf
from tensorflow.keras.preprocessing.image import ImageDataGenerator
from tensorflow.keras.applications import ResNet50
from tensorflow.keras.layers import Dense, GlobalAveragePooling2D
from tensorflow.keras.models import Model
import pandas as pd
import os
from sklearn.model_selection import train_test_split


# Load the ResNet-50 model with pretrained ImageNet weights
base_model = ResNet50(weights='imagenet', include_top=False, input_shape=(224, 224, 3))

# Freeze all layers in the base model to fine-tune only the top layers
base_model.trainable = False

# Add custom layers on top of ResNet-50 for classification
x = base_model.output
x = GlobalAveragePooling2D()(x)
x = Dense(1024, activation='relu')(x)
output = Dense(7, activation='softmax')(x)  # Number of classes

# Create the complete model
model = Model(inputs=base_model.input, outputs=output)
```

Appendix 2.2 Base Model (ResNet-50)



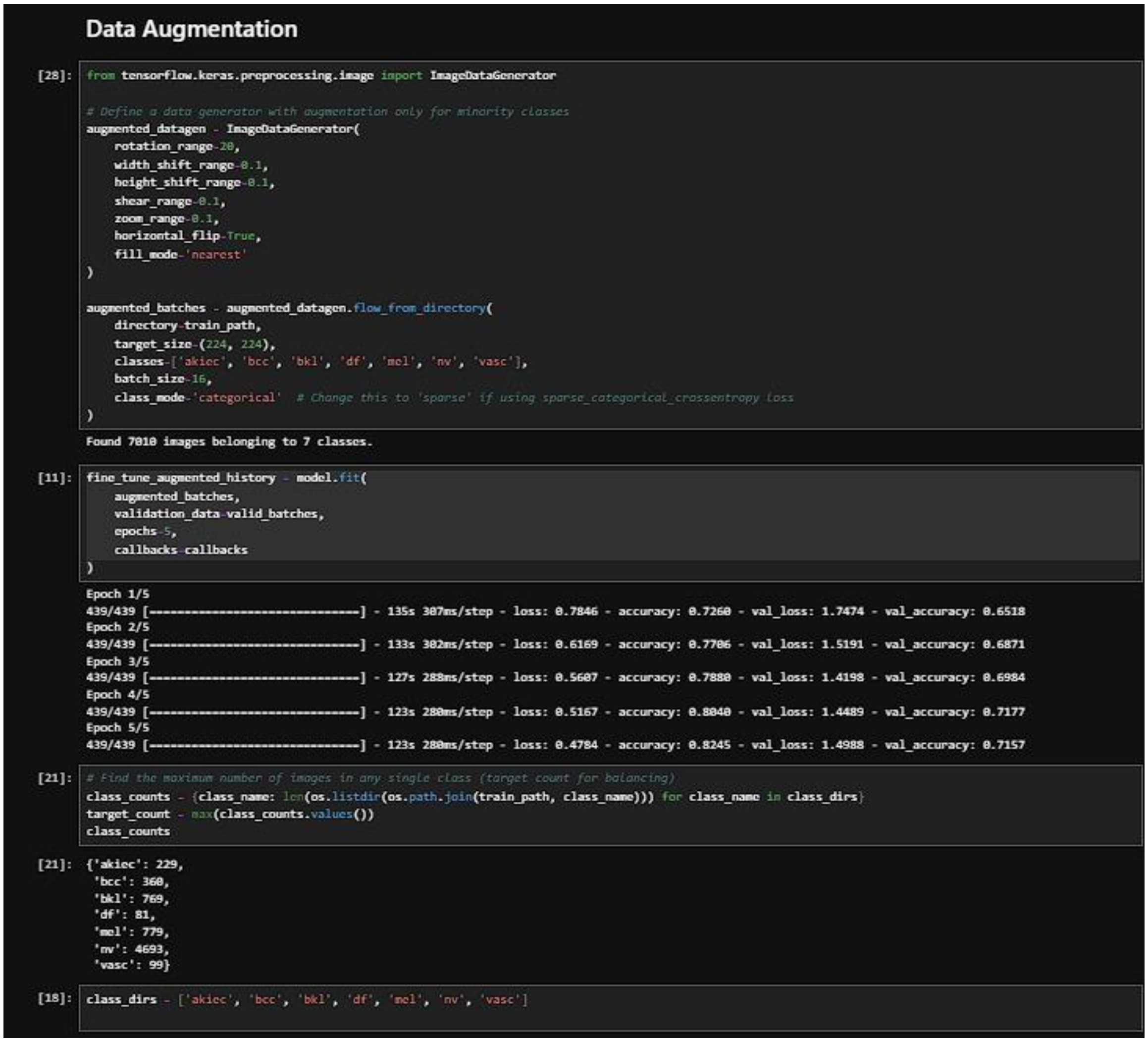
```
[11]: # Train the model with early stopping and model checkpointing
      callbacks = [
          tf.keras.callbacks.EarlyStopping(patience=3, monitor='val_loss'),
          tf.keras.callbacks.ModelCheckpoint('logs/best_model.keras', save_best_only=True, monitor='val_loss')
      ]

      history = model.fit(
          train_batches,
          validation_data=valid_batches,
          epochs=10,
          callbacks=callbacks
      )

      Epoch 1/10
      439/439 [==============================] - 77s 155ms/step - loss: 0.7763 - accuracy: 0.7218 - val_loss: 0.6859 - val_accuracy: 0.7690
      Epoch 2/10
      439/439 [==============================] - 59s 135ms/step - loss: 0.5454 - accuracy: 0.7980 - val_loss: 0.5515 - val_accuracy: 0.7983
      Epoch 3/10
      439/439 [==============================] - 60s 136ms/step - loss: 0.4555 - accuracy: 0.8322 - val_loss: 0.5503 - val_accuracy: 0.7943
      Epoch 4/10
      439/439 [==============================] - 57s 131ms/step - loss: 0.3961 - accuracy: 0.8575 - val_loss: 0.5397 - val_accuracy: 0.8049
      Epoch 5/10
      439/439 [==============================] - 57s 129ms/step - loss: 0.3459 - accuracy: 0.8736 - val_loss: 0.5149 - val_accuracy: 0.8069
      Epoch 6/10
      439/439 [==============================] - 58s 131ms/step - loss: 0.2909 - accuracy: 0.8973 - val_loss: 0.4613 - val_accuracy: 0.8382
      Epoch 7/10
      439/439 [==============================] - 58s 131ms/step - loss: 0.2629 - accuracy: 0.9064 - val_loss: 0.4871 - val_accuracy: 0.8276
      Epoch 8/10
      439/439 [==============================] - 56s 127ms/step - loss: 0.2261 - accuracy: 0.9251 - val_loss: 0.5117 - val_accuracy: 0.8216
      Epoch 9/10
      439/439 [==============================] - 56s 128ms/step - loss: 0.1975 - accuracy: 0.9367 - val_loss: 0.5279 - val_accuracy: 0.8036
```

Appendix 2.3 Training



```
[12]: # Unfreeze the last few layers
      for layer in base_model.layers[-10:]:
          layer.trainable = True

      # Recompile with a lower learning rate
      model.compile(optimizer=tf.keras.optimizers.Adam(learning_rate=1e-5),
                    loss='categorical_crossentropy',
                    metrics=['accuracy'])

      # Fine-tune the model
      fine_tune_history = model.fit(
          train_batches,
          validation_data=valid_batches,
          epochs=5,
          callbacks=callbacks
      )

      Epoch 1/5
      439/439 [==============================] - 61s 131ms/step - loss: 0.2404 - accuracy: 0.9231 - val_loss: 0.4767 - val_accuracy: 0.8395
      Epoch 2/5
      439/439 [==============================] - 57s 129ms/step - loss: 0.1690 - accuracy: 0.9556 - val_loss: 0.4689 - val_accuracy: 0.8422
      Epoch 3/5
      439/439 [==============================] - 57s 129ms/step - loss: 0.1291 - accuracy: 0.9740 - val_loss: 0.4755 - val_accuracy: 0.8442
      Epoch 4/5
      439/439 [==============================] - 58s 132ms/step - loss: 0.1039 - accuracy: 0.9807 - val_loss: 0.4707 - val_accuracy: 0.8462
      Epoch 5/5
      439/439 [==============================] - 57s 131ms/step - loss: 0.0808 - accuracy: 0.9894 - val_loss: 0.4780 - val_accuracy: 0.8482
```

Appendix 2.4 Fine Tuned Model (10 layers)



Data Augmentation

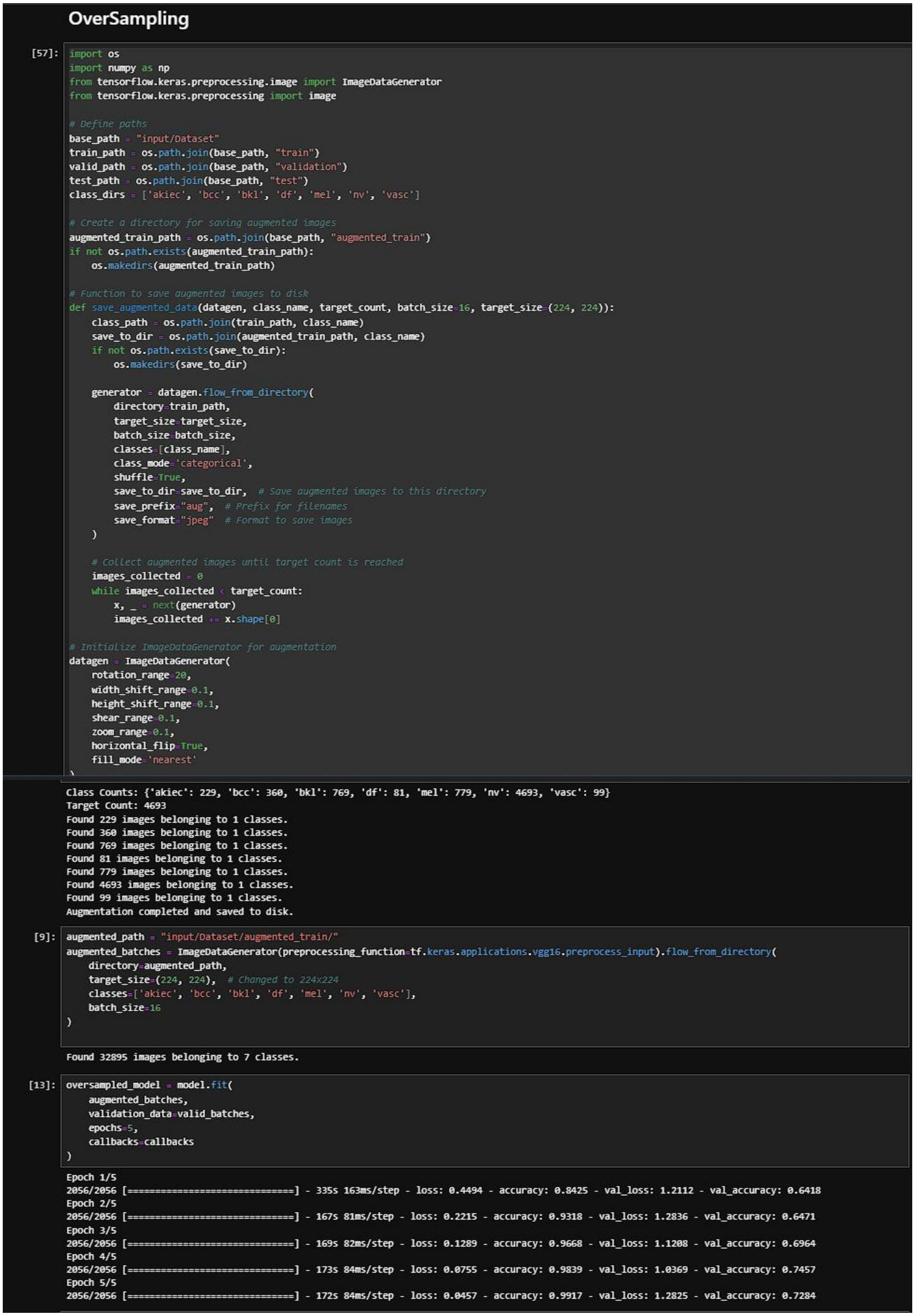
```
[28]: from tensorflow.keras.preprocessing.image import ImageDataGenerator

      # Define a data generator with augmentation only for minority classes
      augmented_datagen = ImageDataGenerator(
          rotation_range=20,
          width_shift_range=0.1,
          height_shift_range=0.1,
          shear_range=0.1,
          zoom_range=0.1,
          horizontal_flip=True,
          fill_mode='nearest'
      )

      augmented_batches = augmented_datagen.flow_from_directory(
          directory=train_path,
          target_size=(224, 224),
          classes=['akiec', 'bcc', 'bkl', 'df', 'mel', 'nv', 'vasc'],
          batch_size=16,
          class_mode='categorical'  # Change this to 'sparse' if using sparse_categorical_crossentropy loss
      )

      Found 7010 images belonging to 7 classes.
```

```
[11]: fine_tune_augmented_history = model.fit(
          augmented_batches,
          validation_data=valid_batches,
          epochs=5,
          callbacks=callbacks
      )

      Epoch 1/5
      439/439 [==============================] - 135s 307ms/step - loss: 0.7846 - accuracy: 0.7260 - val_loss: 1.7474 - val_accuracy: 0.6518
      Epoch 2/5
      439/439 [==============================] - 133s 302ms/step - loss: 0.6169 - accuracy: 0.7706 - val_loss: 1.5191 - val_accuracy: 0.6871
      Epoch 3/5
      439/439 [==============================] - 127s 288ms/step - loss: 0.5607 - accuracy: 0.7880 - val_loss: 1.4198 - val_accuracy: 0.6984
      Epoch 4/5
      439/439 [==============================] - 123s 280ms/step - loss: 0.5167 - accuracy: 0.8040 - val_loss: 1.4489 - val_accuracy: 0.7177
      Epoch 5/5
      439/439 [==============================] - 123s 280ms/step - loss: 0.4784 - accuracy: 0.8245 - val_loss: 1.4988 - val_accuracy: 0.7157
```

```
[21]: # Find the maximum number of images in any single class (target count for balancing)
      class_counts = {class_name: len(os.listdir(os.path.join(train_path, class_name))) for class_name in class_dirs}
      target_count = max(class_counts.values())
      class_counts

[21]: {'akiec': 229,
       'bcc': 360,
       'bkl': 769,
       'df': 81,
       'mel': 779,
       'nv': 4693,
       'vasc': 99}
```

```
[18]: class_dirs = ['akiec', 'bcc', 'bkl', 'df', 'mel', 'nv', 'vasc']
```

Appendix 2.5 Data Augmentation



OverSampling

[57]:

```
import os
import numpy as np
from tensorflow.keras.preprocessing.image import ImageDataGenerator
from tensorflow.keras.preprocessing import image

# Define paths
base_path = "input/Dataset"
train_path = os.path.join(base_path, "train")
valid_path = os.path.join(base_path, "validation")
test_path = os.path.join(base_path, "test")
class_dirs = ['akiec', 'bcc', 'bkl', 'df', 'mel', 'nv', 'vasc']

# Create a directory for saving augmented images
augmented_train_path = os.path.join(base_path, "augmented_train")
if not os.path.exists(augmented_train_path):
    os.makedirs(augmented_train_path)

# Function to save augmented images to disk
def save_augmented_data(datagen, class_name, target_count, batch_size=16, target_size=(224, 224)):
    class_path = os.path.join(train_path, class_name)
    save_to_dir = os.path.join(augmented_train_path, class_name)
    if not os.path.exists(save_to_dir):
        os.makedirs(save_to_dir)

    generator = datagen.flow_from_directory(
        directory=train_path,
        target_size=target_size,
        batch_size=batch_size,
        classes=[class_name],
        class_mode='categorical',
        shuffle=True,
        save_to_dir=save_to_dir,  # Save augmented images to this directory
        save_prefix="aug",  # Prefix for filenames
        save_format="jpeg"  # Format to save images
    )

    # Collect augmented images until target count is reached
    images_collected = 0
    while images_collected < target_count:
        x, _ = next(generator)
        images_collected += x.shape[0]

# Initialize ImageDataGenerator for augmentation
datagen = ImageDataGenerator(
    rotation_range=20,
    width_shift_range=0.1,
    height_shift_range=0.1,
    shear_range=0.1,
    zoom_range=0.1,
    horizontal_flip=True,
    fill_mode='nearest'
)
```

```
Class Counts: {'akiec': 229, 'bcc': 360, 'bkl': 769, 'df': 81, 'mel': 779, 'nv': 4693, 'vasc': 99}
Target Count: 4693
Found 229 images belonging to 1 classes.
Found 360 images belonging to 1 classes.
Found 769 images belonging to 1 classes.
Found 81 images belonging to 1 classes.
Found 779 images belonging to 1 classes.
Found 4693 images belonging to 1 classes.
Found 99 images belonging to 1 classes.
Augmentation completed and saved to disk.
```

[9]:

```
augmented_path = "input/Dataset/augmented_train/"
augmented_batches = ImageDataGenerator(preprocessing_function=tf.keras.applications.vgg16.preprocess_input).flow_from_directory(
    directory=augmented_path,
    target_size=(224, 224),  # Changed to 224x224
    classes=['akiec', 'bcc', 'bkl', 'df', 'mel', 'nv', 'vasc'],
    batch_size=16
)
```

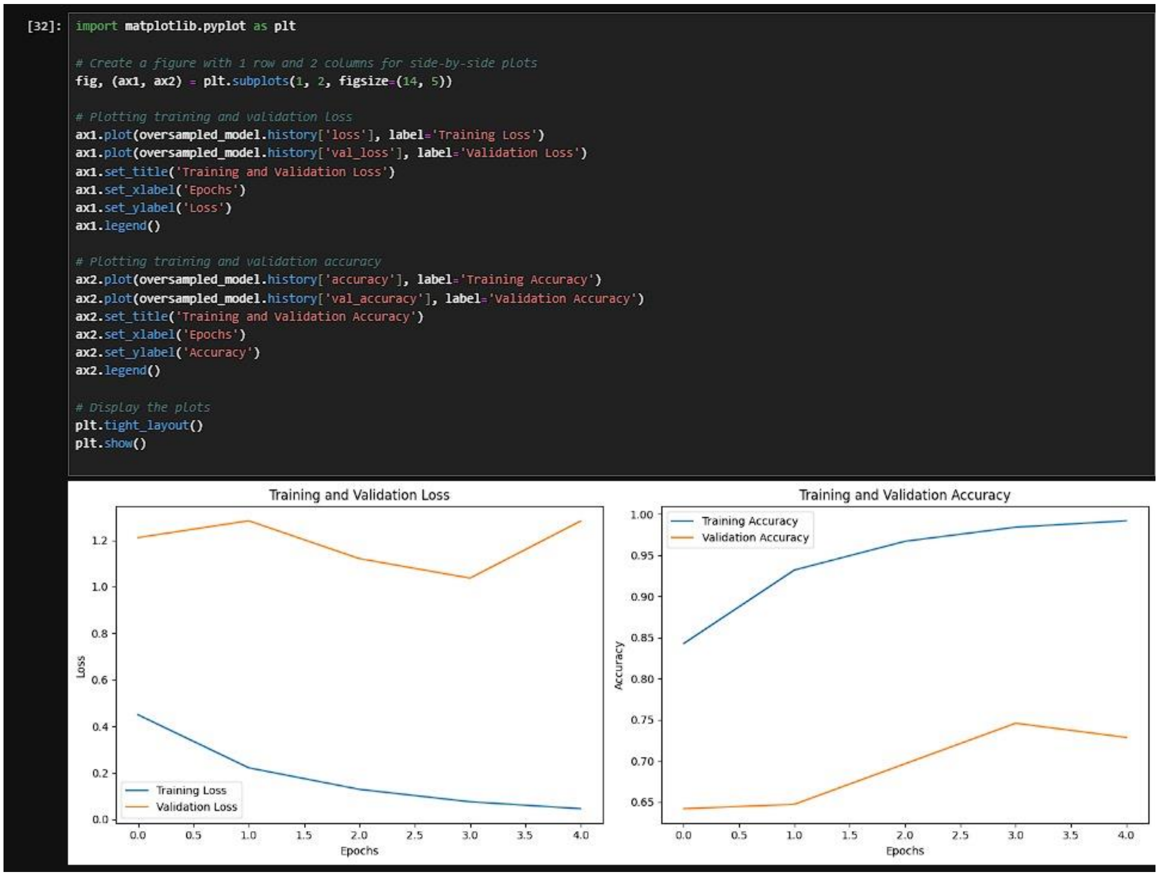
```
Found 32895 images belonging to 7 classes.
```

[13]:

```
oversampled_model = model.fit(
    augmented_batches,
    validation_data=valid_batches,
    epochs=5,
    callbacks=callbacks
)
```

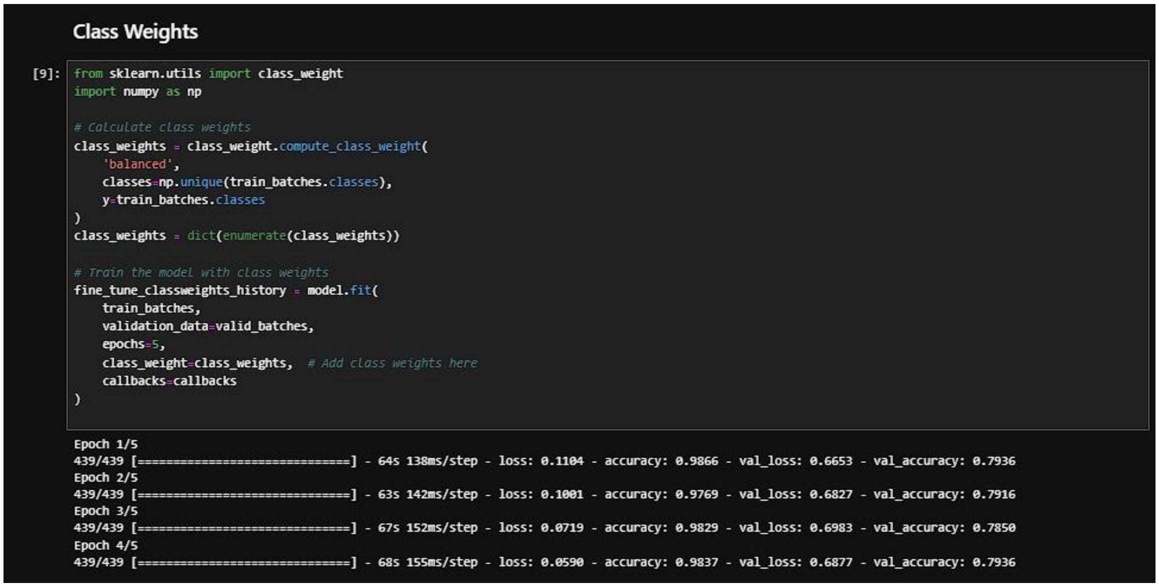
```
Epoch 1/5
2056/2056 [==============================] - 335s 163ms/step - loss: 0.4494 - accuracy: 0.8425 - val_loss: 1.2112 - val_accuracy: 0.6418
Epoch 2/5
2056/2056 [==============================] - 167s 81ms/step - loss: 0.2215 - accuracy: 0.9318 - val_loss: 1.2836 - val_accuracy: 0.6471
Epoch 3/5
2056/2056 [==============================] - 169s 82ms/step - loss: 0.1289 - accuracy: 0.9668 - val_loss: 1.1208 - val_accuracy: 0.6964
Epoch 4/5
2056/2056 [==============================] - 173s 84ms/step - loss: 0.0755 - accuracy: 0.9839 - val_loss: 1.0369 - val_accuracy: 0.7457
Epoch 5/5
2056/2056 [==============================] - 172s 84ms/step - loss: 0.0457 - accuracy: 0.9917 - val_loss: 1.2825 - val_accuracy: 0.7284
```

Appendix 2.6 OverSampling



```
[32]: import matplotlib.pyplot as plt

      # Create a figure with 1 row and 2 columns for side-by-side plots
      fig, (ax1, ax2) = plt.subplots(1, 2, figsize=(14, 5))

      # Plotting training and validation loss
      ax1.plot(oversampled_model.history['loss'], label='Training Loss')
      ax1.plot(oversampled_model.history['val_loss'], label='Validation Loss')
      ax1.set_title('Training and Validation Loss')
      ax1.set_xlabel('Epochs')
      ax1.set_ylabel('Loss')
      ax1.legend()

      # Plotting training and validation accuracy
      ax2.plot(oversampled_model.history['accuracy'], label='Training Accuracy')
      ax2.plot(oversampled_model.history['val_accuracy'], label='Validation Accuracy')
      ax2.set_title('Training and Validation Accuracy')
      ax2.set_xlabel('Epochs')
      ax2.set_ylabel('Accuracy')
      ax2.legend()

      # Display the plots
      plt.tight_layout()
      plt.show()
```

Appendix 2.7 OverSampling Result

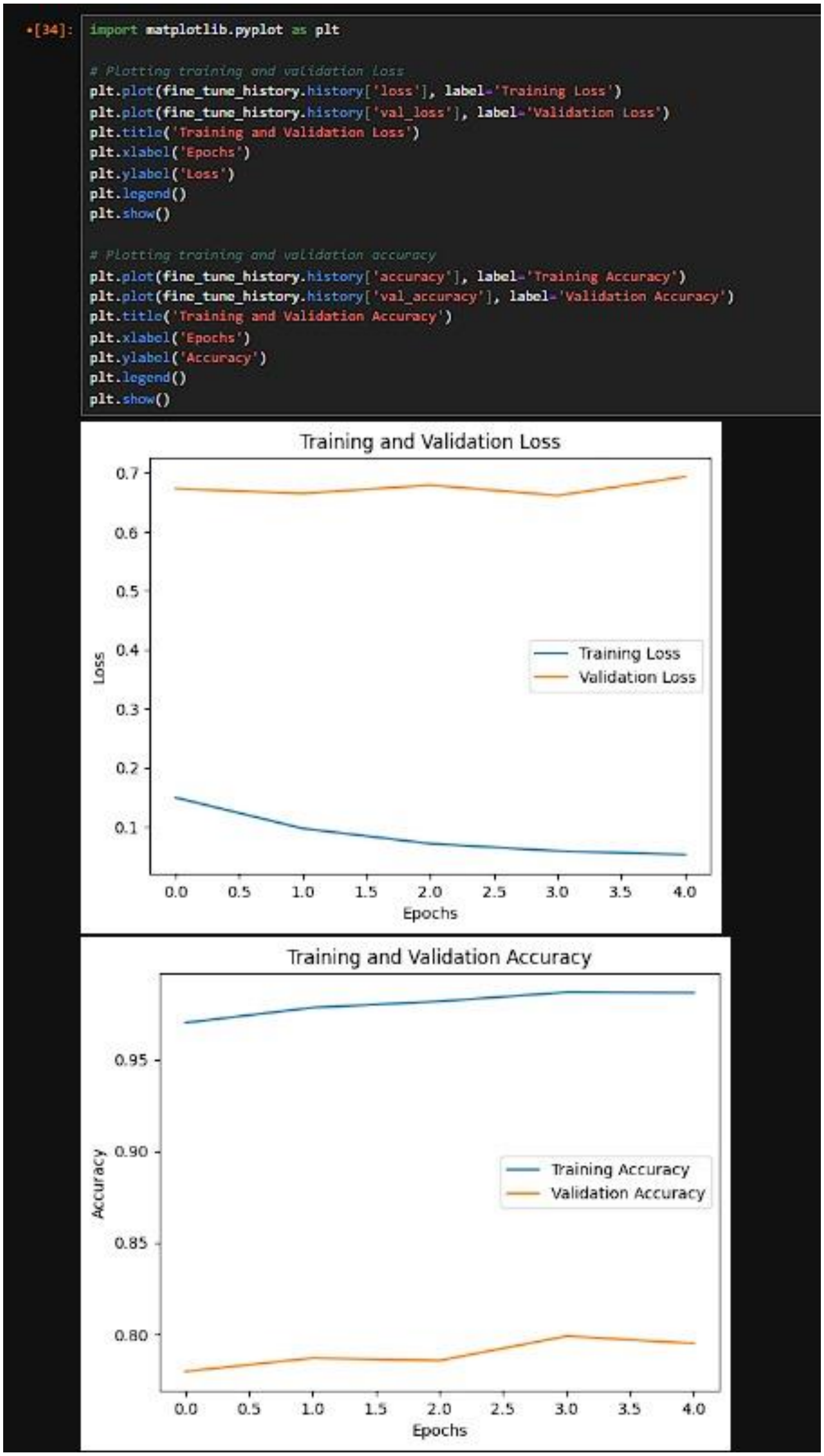


Class Weights

```
[9]: from sklearn.utils import class_weight
     import numpy as np

     # Calculate class weights
     class_weights = class_weight.compute_class_weight(
         'balanced',
         classes=np.unique(train_batches.classes),
         y=train_batches.classes
     )
     class_weights = dict(enumerate(class_weights))

     # Train the model with class weights
     fine_tune_classweights_history = model.fit(
         train_batches,
         validation_data=valid_batches,
         epochs=5,
         class_weight=class_weights,  # Add class weights here
         callbacks=callbacks
     )
```

```
Epoch 1/5
439/439 [==============================] - 64s 138ms/step - loss: 0.1104 - accuracy: 0.9866 - val_loss: 0.6653 - val_accuracy: 0.7936
Epoch 2/5
439/439 [==============================] - 63s 142ms/step - loss: 0.1001 - accuracy: 0.9769 - val_loss: 0.6827 - val_accuracy: 0.7916
Epoch 3/5
439/439 [==============================] - 67s 152ms/step - loss: 0.0719 - accuracy: 0.9829 - val_loss: 0.6983 - val_accuracy: 0.7850
Epoch 4/5
439/439 [==============================] - 68s 155ms/step - loss: 0.0590 - accuracy: 0.9837 - val_loss: 0.6877 - val_accuracy: 0.7936
```

Appendix 2.8 Class Weights



```
•[34]: import matplotlib.pyplot as plt

       # Plotting training and validation loss
       plt.plot(fine_tune_history.history['loss'], label='Training Loss')
       plt.plot(fine_tune_history.history['val_loss'], label='Validation Loss')
       plt.title('Training and Validation Loss')
       plt.xlabel('Epochs')
       plt.ylabel('Loss')
       plt.legend()
       plt.show()

       # Plotting training and validation accuracy
       plt.plot(fine_tune_history.history['accuracy'], label='Training Accuracy')
       plt.plot(fine_tune_history.history['val_accuracy'], label='Validation Accuracy')
       plt.title('Training and Validation Accuracy')
       plt.xlabel('Epochs')
       plt.ylabel('Accuracy')
       plt.legend()
       plt.show()
```

Appendix 2.9 Class Weights Result