SKIN CANCER DETECTION

Dissertation submitted in fulfilment of the requirements for the Degree of

BACHELOR OF TECHNOLOGY

in

COMPUTER SCIENCE AND ENGINEERING

By

Arindam Singh Thakur 12017006

Supervisor

Ms. Shivangini Gupta

School of Computer Science and Engineering

Lovely Professional University

Phagwara, Punjab (India)

April,2023

ABSTRACT

The objective of getting the most accurate diagnosis out of the medical imaging, discriminating skin cancer with an image processing method leads us to the required efficiency. For example, the diagnostic phase is a vital one, given that the availability of correct medication is dependent on it and the course of treatment is based on this factor. On the other hand, the growing job responsibilities due to the challenge leads to a long queue of unending and untreated conditions. This critical deficiency of resources has precipitously made search for latest available solutions that aim at improving the diagnostic techniques imperative.

Besides, the extraction of data that is solely linked to skin lesion diagnosis from different medical databases possesses many other hurdles in the skin lesion diagnosis. For example, the data levels range from tumor size cases to complexity degrees and since these factors contribute in diverse forms to the imbalances that may exist, they may have a distorting effect on the accuracy of machine learning algorithms. The answer might be done by inventing new artificial intelligence technology and also launching the program that exclusively works for the analysis of melanoma.

In order to deal with these new problems, scientists are increasingly using powerful analytical methods such as artificial intelligence combined with machine learning. Besides, one another class imbalance in data, that some classes are underrepresented in the training data, is one of principle hindrance to the use of deep learning approaches. Although this challenge exists, creative ideas are elaborated including constructing new algorithms and methods for neural net brains training.

This paper is focused on discovering a feasible solution to the multifarious challenges of class imbalance in skin lesion diagnosis. Utilizing deep learning algorithms in our program for the training process will be a relief to the accuracy and the speed of disease diagnosis. Here, we explore the possibilities and limitations of AI in terms of improving the quality of care for all patients on a global scale by incorporating all available methods.

As well as providing a solution for data imbalance, this research will encompass an aspect of leveraging deep learning models for effective and fast skin cancer diagnosis improvement. Acting as a second glance before making the final decision, these algorithms can analyze the big number of skin disease related images and reveal very deep specific patterns and features. The process of our approach entails intensive testing for validation and the development of steadfast and effective diagnosing tools that healthcare professionals can employ to facilitate the decision-making processes. In conclusion, the future of dermatology lies in the integration of new technologies, bridging various disciplines together. We want to lead the field by applying and testing new approaches to diagnose skin cancer in an effort to revolutionize the whole process.

Keywords: skin cancer, lesions, prediction, CNN, deep learning, HAM10000 dataset, imbalance, sampling techniques, transfer learning, VGG, ResNet, evaluation metrics, deployment, Streamlit, image classification, data augmentation, classification report

DECLARATION STATEMENT

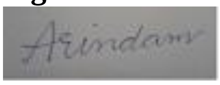
I hereby declare that the research work reported in the dissertation/dissertation proposal entitled "Skin Cancer Detection" in partial fulfilment of the requirement for the award of Degree for Bachelor of Technology in Computer Science and Engineering at Lovely Professional University, Phagwara, Punjab is an authentic work carried out under supervision of my research supervisor Mrs. Shivangini Gupta. I have not submitted this work elsewhere for any degree or diploma.

I understand that the work presented herewith is in direct compliance with Lovely Professional University's Policy on plagiarism, intellectual property rights, and highest standards of moral and ethical conduct. Therefore, to the best of my knowledge, the content of this dissertation represents an authentic and honest research effort conducted, in its entirety, by me. I am fully responsible for the contents of my dissertation work.

Name of candidate
Arindam Singh Thakur

Registration No.
12017006

Sig.



SUPERVISOR’S CERTIFICATE

This is to certify that the work reported in the B.Tech Dissertation/dissertation proposal entitled “**Skin Cancer Detection”**, submitted by **Arindam Singh Thakur** at **Lovely Professional University, Phagwara, India** is a bonafide record of his / her original work carried out under my supervision. This work has not been submitted elsewhere to any other degree.

Signature of Supervisor

(Name of Supervisor)

Date:

Counter Signed by:

1) **Concerned HOD:**
   HoD’s Signature: ________________

   HoD Name: ____________________

   Date: ___________________

2) **Neutral Examiners:**

   External Examiner

   Signature: _______________

   Name: __________________

   Affiliation: ______________

   Date: ___________________

   Internal Examiner

   Signature: _______________

   Name: __________________

   Date: ___________________

ACKNOWLEDGEMENT

First of all, I would like to thank everyone who has provided me with the necessary inputs in my efforts to make work skin cancer detection using Convolutional Neural Networks. Our success story would have never been written without the help and direction from many people and groups.

Firstly, I would like to express my sincere gratitude to my supervisor Mrs. Shivangini Gupta for their invaluable contributions and guidance which made our project accomplished. Acquiring constructive comments and favorable advice over this period of time has been a catalyst for its implementation. In addition, I would like to thank the faculty and classmates who have shared with us beneficial comments and tips. Their input has assisted us in defining the necessary changes and in tuning the performance of our model.

We are grateful to Harvard Dataverse for giving access to The HAM10000 image dataset, a collection of multi-sources dermatoscopic images of many different common pigmented skin lesions that was used in the development of this project.

In addition, I appreciate the efforts of the developer behind the open-source libraries and frameworks utilized in the actual development of this project. Such packages are Python, NumPy, Pandas, Scikit-learn, nltk, TensorFlow & Streamlit, among other many others. This technology has prompted accuracy as well as the efficiency of the tactics, which are incorporated in the system.

Last but not least, I wish to give acknowledgments to the Harvard Dataverse , the source of data that I used to construct the skin cancer detection model. We have deeply appreciated the staff's careful management of the data files that have been instrumental in this endeavor.

In the end, we would like to have a special thank you anyone who had contributed to this project.

TABLE OF TOPICS

CONTENTS	PAGE NO.
Cover Page	i
PAC form	ii
Abstract	iii
Declaration	iv
Supervisor’s Certificate	v
Acknowledgement	vi
Table of Contents	vii
List of Acronyms / Abbreviations (If any)	viii
List of Figures	ix
List of Tables	x

TABLE OF CONTENTS

CONTENTS **PAGE NO.**

CHAPTER 1: INTRODUCTION

1.1 Background and Motivation
1.2 Problem Statement
1.3 Objectives and Goals
1.4 Scope of the Study
1.5 Significance of Skin Cancer Detection

CHAPTER 2: LITERATURE REVIEW

2.1 Overview of Skin Cancer Classification
2.2 Previous Studies on Skin Lesion Detection
2.3 Unbalanced Datasets in Medical Imaging
2.4 Pretrained Models
2.5 Evolution of Diagnostic Technologies in Dermatology

CHAPTER 3: METHODOLOGY

3.1 Data Collection and Description
3.2 Data Preprocessing
  3.2.1 Image Resizing and Normalization
  3.2.2 Data Augmentation
  3.2.3 Balancing the Dataset
3.3 Model Architecture Selection
  3.3.1 Convolutional Neural Network Design
  3.3.2 Transfer Learning Approach
3.4 Training Setup and Hyperparameter Tuning

CHAPTER 4: EXPERIMENTAL RESULTS

4.1 Exploratory data Analysis
4.2 Training Process and Model Performance
4.3 Comparison of Different Models
4.4 Impact of Sampling Techniques on Performance
4.5 Analysis of Evaluation Metrics

CHAPTER 5: MODEL DEPLOYMENT

5.1 Deployment Platforms and Considerations
5.2 Integration with Web Applications
5.3 User Interface Design for Skin Lesion Detection

CHAPTER 6: DISCUSSION AND CONCLUSION

6.1 Summary of Findings
6.2 Contributions of the Study
6.3 Limitations and Future Directions

REFERENCES

LIST OF TABLES

TABLE NO.	TABLE DESCRIPTION	PAGE NO.
Table 4.1	Comparison of models	46

LIST OF FIGURES

FIGURE NO.	FIGURE DESCRIPTION	PAGE NO.
Figure2.1	Count of classes in dataset	19
Figure2.2	VGG16 Architecture	21
Figure2.3	MobileNet Architecture	22
Figure2.4	ResNet Architecture	23
Figure2.5	DenseNet121 Architecture	24
Figure3.1	Skin cancer Types	27
Figure3.2	Data Preprocessing	28
Figure3.4	Data Augmentation	30
Figure3.5	CNN Network	33
Figure3.6	Transfer Learning	34
Figure3.7	Training Setup	35
Figure4.1	Null Values	37
Figure4.2	Localization Distribution by sex	38
Figure4.3	Localization of Skin Cancer by Sex	38
Figure4.4	Percentage of male and female cancer Patients	39
Figure4.5	Frequency of lesion type	39
Figure4.6	Distribution of Age by Lesion Type	40
Figure4.7	Training and Validation Accuracy	41
Figure4.8	Training and Validation Loss	41
Figure4.9	VGG16 Used	42
Figure4.10	Mobilenet used	42
Figure4.11	Densenet used	43
Figure4.12	ResNet used	43
Figure4.13	Confusion Matrix	45
Figure4.14	Classification Report	45
Figure5.1	Model Tabs	48
Figure5.2	Model Upload	48
Figure5.3	Model Output	49

CHAPTER 1: INTRODUCTION

Skin cancer is a disease that is caused due to exposure to sun UV rays for a prolonged period of time. This disease is rapidly growing on a global scale and is becoming a great concern to society. Due to scarcity in health care resources it is necessary to incorporate various methods and upcoming technology to tackle this problem in an efficient way possible. So, to incorporate new technology in process to tackle this problem Deep learning can be used, as CNN(Convolutional Neural Networks) in particular has shown potential with a high degree of precision in image classification tasks, like VGG16,have been trained in large datasets . Studies using HAM10000 dataset show that transfer learning has enhanced the CNN Model’s performance in categorizing skin cancer. The majority of the skin cancer disease related death are caused due to the melanoma category ,which is one type of a skin cancer that offers a serious health problem to the person suffering from skin cancer. Over the past ten years there has been a sudden spike in skin cancer falling under the category of melanoma skin cancer, requiring the early identification and categorizing of the patient in various category for the prevention and medication of the patient .

And consequently, deep learning, AI, and other machine learning technologies have been found to be more precise than traditional techniques by increasingly higher numbers. Convolutional Neural Networks (CNNs) are a vital technique that facilitates the physician's diagnosis process, and they help classify the different types of skin cancer. Whereas the computational power of human experts is still surpassed by those of GPUs in deep learning models despite the high data requirement, the latter have shown better accuracy in correct skin cancer diagnosis.
The mortality rates of skin cancer are quickly becoming one of the leading causes of death across the globe. Accrediting factors go hand in hand with ancestry and, but exposure to ultraviolet or other types of radiation, as well as the lifestyle choices made . As all early tumors have a distinct variation of symptoms, often requiring biopsy and other invasive diagnostic methods to ascertain the type and nature of the tumor. Through image processing digital studies, computer aided diagnosis (CAD) systems have shown what it would be like to improve early melanoma screenings. This will make the surgeon’s work easier by giving the necessary data on this treatment. This mostly is based on accurate identification of the form of skin cancer because misdiagnosis can lead to incorrect treatment. When joined with hybrid method as well as transfer learning in DCNNs, they have proven to be impressively precise in the classification of skin cancer. According to the research studied, the use of Computer Aided Design system, which employs pre-trained DCNN architecture and advanced convolution's, has shown great promise in detecting cancer in the early stages.
Basically, early cancer detection and classification when deep learning and artificial intelligence are combined with the diagnosis for skin cancer shows lots of potential with respect to improving clinical outcomes.

1.1 Background and Motivation :

Skin cancer detection model creation based on Convolutional Neural Networks (CNNs) is of a high importance at the moment due to growing healthcare diversification demands. Skin cancer is one of the diseases which are being seen more often worldwide with melanoma being the most dangerous type of skin cancer attributed by its ability to invade other parts of the body if not detected early. However, early diagnosis paves the way for a more favorable prognosis and successful treatment entirely.
Here's some background and motivation behind the development of such a model:

Rising Incidence: Skin cancer is one of the top prevalent cancer forms among modern people, notably due to factors like excessive UV exposure from the sun and, of course, from man-made sources. This, consequently, contributed to the increased demand for diagnostics with high precision and a very good quality.

Limited Access to Dermatologists: In a lot cases, patients are poorly accessed by the dermatologists or specialized health facilities, therefore they are not timely diagnosed or such an early interventions are missed. Automated detection models offer an aggressive measure towards this gap by designing screening tools that are easily accessible.

Visual Diagnosis Challenges: A skin lesion diagnosis is often difficult not only for inexperienced people but also for experienced dermatologists without assistance from modern techniques. A skin lesion can look very different from its benign and malignant counterparts, sometimes making it difficult to distinguish between the two. Due to the subjective nature and margin of error involved, errors can easily occur. CNN-based models seem as the way out from the situation because of the use of large data sets which teach the network patterns and characteristics that can be associated with cancerous lesions.

Advances in Deep Learning: CNNs (Convolutional Neural Networks), a type of deep learning models, has recently demonstrated great potential in several image recognition assignments, such as medical image detection. The fashion that Lifetime has built in hierarchical representations features automatically from raw data has made them perfectly fit for tasks like detecting skin cancers where features in images are predispositions.

Potential for Early Detection: Early detection is of utmost importance to increasing survival rates and the reducing the cancer morbidity the world over. The CNN-based models can act as an assistant to identify suspicious lesions in images, thus, an early cancer detection that enables timely treatment and intervention.

Cost-Effective Screening: The use of automated skin cancer detection models can be an important factor in making the screening methods relatively cheaper than traditional types. After having been created, these products can be deployed on systems that are widely spread on handheld mobile devices or integrated into public health systems, making screening more accessible and available for a wider population.

Research and Innovation: Skin cancer detection models based on convolutional neural networks (CNNs) have created a convergence arena where medical research, computer vision, as well as machine learning converge. A further development of these algorithms or models may lead to the emergence of more complex and efficient versions that obviously will produce better outcomes for patients and the healthcare systems in the whole world.

1.2 Problem Statement :

Given that skin cancer detection is a problem based on CNNs and pertains to the shortcomings of the prevailing diagnosis procedures, particularly in relation to early detection and wider healthcare products, the statement of the problem will be the limitations and challenges, as it is a milestone in the advancement of skin cancer prognosis. Modern medicine and its imaging techniques have greatly evolved, and now diagnostic procedures tend to be more precise. However, the visual investigation of the skin areas remains a subjective process with a high rate of errors even in the most experienced specialists, consequently, the diagnostic may be delayed, and the treatment outcomes may be sub-optimal. This is yet more complicated by issues similar to rising cases of skin cancer, lack of dermatologist, and special problem of healthcare facilities in some places and affordability of screening methods.

One of the main problems involves constructing a computer program that can correctly discriminate many different lesions from pictures accordingly, that is, to facilitate an early diagnosis and prompt treatment. Prevalent methods, for instance, the visual examinations by dermatologists and dermatoscopy have built-in limitations like subjectivity and the dependence on human beings' visual acuity. Specialist training and sophisticated equipment are also needed. Besides, the number of patients needing dermatological expertise frequently exceeds the available supply of the resources, resulting in the inequalities in the traditional diagnosis and therapy, where the society with poor background or living in the rural area gets affected that are from the greater community.

For dealing with these challenges this project plan is driven by the features of deep neural networks, particularly Convolutional Neural Networks (CNNs), which are to be used in skin cancer detection tools. A huge amount of work has been done by CNNs in the task of image recognition, starting with medical image analysis and ending with feature map creation through the approach that offers data-driven learning of hierarchical representations. With the help of CNN models trained on large the datasets of annotated images of skin lesion, it is possible to construct the good and specific system which classifies and differentiates between benign and malignant lesions on high specifically sensitivity.

Nevertheless, the cited technical and practical considerations need to be infused during the process of the outline of the model of the skin cancer detection using CNN. Some of these considerations are how to create good data sets and labels, how to select the best model architecture and fine-tuning, how to validate and perform future improvement, dealing with the existing healthcare system, regulation, and the ability of the model to scale up and deployment for real-world practicality. To mention some ethical factors such as cognitive approach, patient privacy and informed consent as well as transparency in decision making are in the top priority in the process of evidence-based AI-based healthcare solutions developing and deploying.

In short, the successful construction and the use of a CNN-based skin cancer detection model have the possibility to significantly increase the overall early detect the illnesses rates among individuals, reduce the numbers of deaths and sicknesses linked with the skin cancer as well as widen the accessibility to early diagnosis and treatment. This is beneficial to the health of individuals and communities globally.

1.3 Objectives and Goals:

The objective of the skin cancer detection project based on Convolutional Neural Networks (CNNs) is to construct the robust and accurate automatic system for early diagnosis and discrimination of the skin abnormalities with the main idea to improve health prospects, reduce the morbidity and fatality related to skin cancer and increase the access to the timely medical care. In order to implement this goal, a strategic set of general aims and the steps to reach them have been devised with regards to the research, development, validation and the application.

Data Collection and Curation: The first goal will be to use a differentiated and multicultural database of skin cancer images that contains various images of several skin lesions including the different skin tones and clinical scenarios. This dataset has to be crafted and annotated at the highest grade by dermatologists for scoring the accuracy and credibility of CNN models to learn the disease.

Model Development and Optimization: The attention base lies on creating and improving CNN architecture systems for skin cancer detection, which consider receptor potential, information extraction, computational efficiency, and so on. In addition to maximizing accuracy, this objective also covers the study of methods like transfer learning and data augmentation to make use of pre-trained models and training for healthy model generalization.

Training and Evaluation: The targeted objective is to teach the CNN models on the annotated datasets by using the right optimization algorithms and relevant validation approaches in an attempt to maximize the key performance metrics like sensitivity, specificity, accuracy and area under the ROC curve. Impeccable procedure of evaluation and validation are a must across the model to determine the robustness, generalization capability and clinical use across different patient groups and settings.
Interpretability and Explainability: Being the delicate element of the medical fine-tuning process, the project is going to incorporate explainability and interpretability mechanisms into the CNN models so as to guarantee the transparency of the models' predictions by clinicians and patients.
Validation and Clinical Trials: The aim of the project is to validate the effectiveness and clinical significance of an HCP-run skin cancer detection system based on convolutional neural networks (CNNs) by conducting detailed clinical trials and validation studies that would involve the participation of dermatologists, pathologists, and other healthcare professionals. Such studies evaluate the machine's performance in actual healthcare settings, effect on diagnostic accuracy, patient outcomes and healthcare resource use, as well as its acceptance and usability from the perspective of end users.
Ethical and Regulatory Considerations: These ethical points of patient’s privacy, informant consent, data security and AI deployment responsibility are crucial throughout the project. The objective is to uphold the regulation standards that are compulsory and principles of beneficial Ness, non-maleficence, autonomy, and justice.

The ultimate objective of skin cancer detection project will be realized by addressing all mentioned objectives and goals, and promoting development and progress of AI application in dermatology and healthcare in general. As a consequence, it will have beneficial effect on early detection and prevention of skin cancer, patient care and saving lives.

1.4 Scope of Study :

This project will cover in-depth research of all points related to the technical process of construction, clinical validation, and practical aspects of implementing a computer-aided system for automated diagnosis of skin cancer based on CNNs. This includes:

Data Acquisition and Preprocessing: The study comprises several stages which include but not limited to the development of a large and diversified image dataset of skin lesions via multiple sources, including medical databases, research archives and healthcare institutions. The pipeline involves different activities like image normalization, resizing, and augmentation which are done to improve the dataset quality and handle the cases that do not have the same number of examples.
Model Architecture Design: The research covered uses wide range of convolutional neural network architectures such as ResNet, Inception, and DenseNet. Among then some of the classical models such as VGG-16 and Inception-V3 has been tested as well. The aim is to instruct coding structures in order to make skin cancer detection faster, taking into account things like depth and receptive field, as well as computational efficiency.
Training and Optimization: The study entails training the CNN models using the dataset being annotated with application of the relevant optimization playbook and hyperparameters. The behavior of such methodologies as transfer learning and parameter fine-tuning, which allows pre-trained models to be employed and the rate of convergence and generalization performance to be increased, are the subject of thorough consideration.

Performance Evaluation: An evaluation method that is robust and has a model to review the performances of the trained CNN model also used. The metrics based on sensitivity, specificity, accuracy, precision, recall, and F1-score etcetera, are generated by using cross-validation and hold-out validation approaches. Interpretability and Explainability: The study integrates reading of and explanation of CNN's model used along interpreting of the CNN's model decisions to improve the transparency and the trust in those decisions. Here the process of envisioning the feature maps, getting the saliency maps, and examining the attention mechanism could help give a guide to the how the model operates.
Clinical Validation: Clinical trials were done in order to know the effectiveness and healthcare value the CNN-based application of the skin cancer detection system. Outcomes requires to bind together with dermatologists, pathologists as well as other healthcare professionals which assists in assessing the system's functioning in real-time clinical settings and also its impact on the precision of diagnostics as well as on the patients' results.
Integration and Deployment: The paper touches upon the issues of integrating this model-type CNN model into current clinical systems (for instance, EHRs or mobile applications) in order to achieve a smooth system implementation and clinical workflows. Technical aspects such as scalability, interoperability, and compliance are given focus to guarantee the peaceful and problem-free deployment.
The aim of the this study is encapsulated by taking the specified factors into account. This study thus seeks to advance the detection technology of skin cancer, and in turn improve patient-based care and outcomes in dermatology.

1.5 Significance of Skin Cancer Detection :

The importance of skin cancer detection cannot but be stressed, because of its too bad influence on public health, individual well-being and healthcare systems.

Early Detection Saves Lives: The main benefit of early skin cancer detection is that it enhances treatment success rate and increases survivorship. The deadliest form of skin cancer, melanoma, can be cured with a high specificity if diagnosed and treated in the earliest possible stage. Timely detection whether through screening and diagnostic tools to prevent the progression of the disease and lower death rates.
Prevention and Risk Reduction: Skin cancer screening is a preventive medicine method aimed at early recognition of patients with a higher chance for cancer development and encourages people follow the rules of sun protection and change their behavior. The main advantage of early detection is timely intervention and implementation of preventive schemes like regular skin examinations, sunscreen use, protective clothing, and avoiding wide-exposure to UV radiation.

Reduced Morbidity and Disability: The diagnostics of skin cancer in advanced stages have a high morbidity potential and may result in disfigurement, functional impairment, and diminished quality of life. Early identification provides less invasive treatment procedures, which in turn reduces surgery time and psychological and physical traumas experienced by patients.
Healthcare Resource Optimization: The timely detection of skin cancer has an implication on the distribution of healthcare efforts as it spares the system from the strain of delayed diagnoses and intricate treatment measures. Screening campaigns screen the high-risk groups that lower the chances of late detection and so high-cost treatment and hospitalization will no longer be necessary.
Public Health Impact: Initiatives for the early detection of skin cancers also have implications for public health, which include raising public awareness of safe sun practices, encouraging early

detecting methods, and lessening health inequalities. Through identifying the preventable risk elements and promoting the early step bound of the problem, the skin cancer detection undertakings therefore show their efficiency in the health promotion and diseases prevention. Economic Benefits: Early diagnosing and treatment of skin cancer are responsible for substantive monetary savings through cutting on healthcare expenditures related to management in the advance stage and improving working productivity via the timely return to work. In the first place, prevention and early detection long-term reduction in these costs as the economic burden of the therapy of the advanced stage cancers can be avoided.
Technological Advancements: Slew of developments in the field of skin cancer detection through usage of AI and CAD based deep learning algorithms look set to change the early detection means. These novel developments will help to increase the accuracy, efficiency, and even access to screening resources, especially in regions where dermatological services are unavailable.

Thus, skin cancer detection proves to be an instrument to eliminate excess pain and death, as well as to implement health campaigns, optimize current and public health practice, bring in economic gains. Delving the obstacles that cause access to health care difficult, developing strategies for the early detection of the disease and utilizing the technology development will help society accomplish significant steps in diminishing the burden of skin cancer and health improvement.

CHAPTER 2: LITERATURE REVIEW:

The Skin pigmented lesions has attracted a lot of attention because it has upgraded the efficiency of the skin tone. Large and varied datasets that are used as the basis of the models are difficult to find. Data that can be used covers only a limited number of topics, with limited level of diversity. Ham1000 meant to solve this problem. Over-all, this particular mass of data consists of 10,015 images gathered from a widest possible spectrum of sources and with the use of different techniques .

The dataset includes a tremendous number of diagnostic categories vital for pigmented lesions analysis, e.g., melanoma prevision (mel); pigmented nevi (nv); vascular lesions (vasc); benign keratosis-like lesions (bkl); actinic keratoses and carcinoma intraepithelial (akiec); and basal cell carcinoma (bcc). This dataset unlike other previously available ones is remarkable in the fact that more than half of its lesions are verified by histopathology tests and sources of proof (consensus of experts, in-vivo confocal microscopy, or follow-up study).

In ISIC 2018 competition, the HAM10000 set was used as not only the training set, but also the contribution to either of testing and validation sets. Owing to that, AI machine learning processes have been simplified. There was an overwhelming majority of participants in the challenge who reached the point where they could outperform human experts on the same data set that had initially been corrected by experts at a global level, which underlines the potential of machine learning algorithms in dermatological diagnosis.
Let us mention that as one more finding the dataset has been helpful in exploring the idea of cooperation between humans and machines in the process of medical diagnosis as well. Several studies have given attention to the cases and methods of machine learning in the human-computer interaction formula. They have explicated how medical diagnostics can be benefited from the software algorithms.

Combining human estimation about the images with and without interaction with ResNet50 CNN

discloses the fruits of cooperative strategic methods of increasing diagnostic accuracy.
In addition, binary segmentation masks for every CNN-D case in the HAM10000 dataset have been produced to ensure more effective, in-depth research and assessment. Such masks can evaluation the activation zones of CNN so we can better comprehend how models make the decisions, and this can result on improvement diagnostic algorithm performance.
Overall, the inaugural release of the HAM10000 dataset has notably advanced the condition of the research only based on the automated pigmented skin cancer diagnosis. Because the model is rich in data and complex in nature, machine learning algorithms have effective learning procedures and human-computer interaction in the field of dermatology diagnosis is brought to a higher level.

2.1 Overview of Skin Cancer Classification:

Skin cancer classification is a chief goal in dermatology and medicine – exact skin lesions for diagnosis and treatment. The rising incidence of skin cancer has been observed across the planet and sound classification technique has therefore become an indispensable tool for early diagnosis and treatment.
Classifying skin cancer generally involves either assessing dermatoscopic images or comparing biopsy samples in order to distinguish benign and malignant conditions from other skin lesion. Machine learning and deep learning approaches offer a great contribution for skin cancer classification, making a semi-automatic laptop style scan and reading of dermatoscopic images possible. These algorithms are using images from the large datasets of labeled pictures for training, and they can distinguish the patterns and traits characterizing different skin diseases.
Skin cancer being a disease can be categorized into four types including the melanoma, the basal cell carcinoma, the squamous cell carcinoma, and the benign lesions such as the nevi and the keratoses. The method of identification of each type is based on specific visual signs such as color, texture, shape and border irregularity which are major the factors of accurate classification.
The task of skin cancer classification systems is to distinguish between benign and malignant neoplasms, as well as assign a specific subtype to the malignant neoplasms depending on their histopathological traits. The target is to have accurate classification of the patient’s tumor for clinical decision support, such as biopsy recommendation, treatment planning, and patient prognosis.
Multiple recent innovations that involve artificial intelligence and deep learning have presented impressive achievements in dermatology, leading to skin cancer diagnosis with more efficiency and accuracy. Because of considerable success of deep learning models, especially convolutional neural networks (CNNs), in analyzing the dermoscopic images and recognition of skin anomalies with high levels of sensitivity and specificity, clinicians can rely on those for classification.

2.2 Previous Studies on Skin Lesion Detection:

Previous studies in the skin lesion classification utilizing deep learning methodologies have investigated numerous tendencies to make proper and timely skin disease detection. Popescu et al. applied Convolutional Neural Networks on such dataset as HAM10000 for the purpose of differentiating between skin lesion including melanoma. They used multiple neural networks predict primary tumor subtypes by throwing every pixel of the brain scan classes into them and maintaining a weight matrix specific to the CNN model such that accuracy significantly improved.
Srinivasu' et al. introduces the use of the a hybrid model combining MobileNet and long short-term memory models which makes the skin disease detection system faster. This hybrid method has

achieved an accuracy of 85% on the HAM10000 and has exceeded all the other models in the sentence. Khan and al. designed a mask recurrent neural network (MASK-RNN) for screening skin disease lesions who gained high efficiency on the HAM10000 endowment.
Huang and his team developed a lightweight skin cancer detector applied by deep learning, possessing which said the detector attained an accuracy of 85.8%. The other work of Khan et al. [26] discusses the classifier for multiclass skin lesion on the basis of local color controlled histogram intensity values (LCcHIVs) and reaches the accuracy of 90.67% of the HAM10000 dataset.
Karl and Enrique introduced transfer learning in conjunction with convolutional neural networks for skin cancer detection, whereas Xing et al. proposed a categorical relation preserving contrastive knowledge distillation framework and it outperformed the state-of-the-art method in HAM10000 dataset.
Saket and collegues employed the MobileNet model and a transfer-learning approach in order skin cancer detection, which resulted in 83.1% accuracy on the HAM10000 dataset. Dermoscopic images were used to develop a deep learning-based model by Ameri(specify the data set used and year) and a convolution neural network model from Andronescu et al. for classifying skin cancer. The quality of these studies spotlights the efficacy of deep learning techniques and employing transfer learning approaches that precisely classify skin lesions and recognize skin diseases.

2.3 Unbalanced Datasets in Medical Imaging :

The term uneven data in medical imaging means datasets where one or many classes are more common than others in the dataset. In the current case of skin lesion detection and medical imaging, the imbalanced data occurs when there is a significant difference between the number of images or samples collected in distinct classes of skin lesions.
The disequilibrium in datasets might be related to different reasons, like a rarity of some types of skin lesions compared to others, variations in data collections and biasses in datasets creation process. As instance, infrequent skin conditions or uncommon kind of blemishes has fewer samples available for training compared to common and widespread diseases.
The unbalance of datasets has a range of problems for machine learning algorithms, especially for classification ones. If the dataset is mostly emphasizing specific or classes of a particular class, the model may become biased, predicting the majority class inaccurately. Therefore, it will perform poorly in identifying minority classes. This often takes place when the neural networks can not achieve its optimal performance, which results in reduced effectiveness in real-world applications, especially when the goal is to detect rare conditions as melanoma.

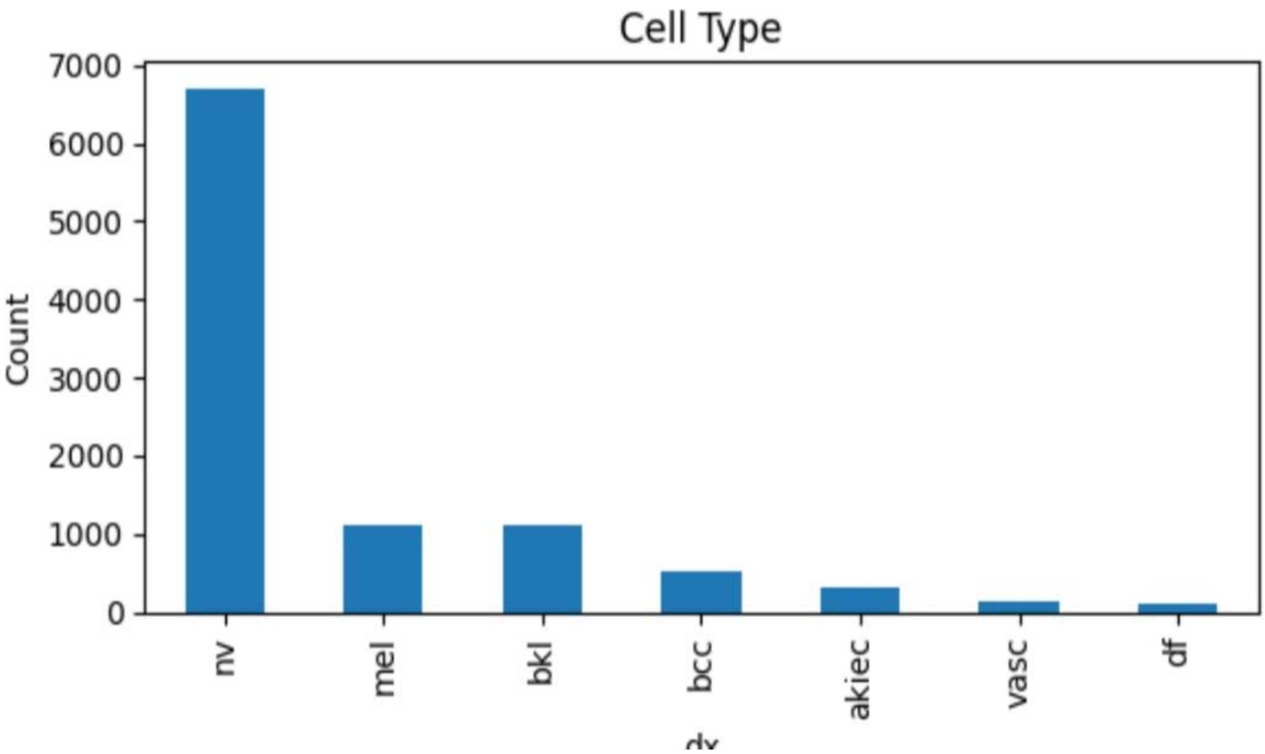


Fig 2.1

Dealing with the unevenness of datasets in medical imaging requires one to take measures that are quite thought-out and specialized. Some of the strategies that researchers and practitioners use for the elimination of class imbalance include data augmentation, resampling strategies (under sampling or oversampling), or utilizing specialized algorithms specifically for the task of handling imbalanced data.

In data augmentation process data size may artificially be increased by introducing real transformations like rotation, flipping, or cropping of existing images. Resampling methods comprise of adjustments of the distribution of samples by either excluding instances from the majority class (under sampling) or keeping instances from the minority class (oversampling) in trying to achieve a balance class distribution.

As well as those, the ensemble approach, the cost-sensitive learning, and also the anomaly detection techniques might help to deal with the imbalanced dataset that talked about, and finally efficiency will be raised in spot the rare or minority classes.

Besides, guaranteeing a proper balance in cases of unbalanced datasets in the medical imaging can be a factor that assures us to have robust and accurate machine learning models not only for skin lesion detection but also for other medical-related applications. Demonstrating process precision and accuracy, researchers can ensure the consistency of their methods and thus achieve their objectives in the clinical application.

2.4 Pretrained Models:

In deep learning pretrained models are models trained using large scale for more general tasks such as image computation, object detection, and natural language processing. After the initial training, they are fine-tuned for more specific tasks or topics. The pre trained models are serving as the base that adds to the efficiency of the system, a big boost to the performance and saves the resource requirement by a lot.

One of the fantastic peculiarities of such models while working with the transfer of information is transfer learning. Oftenly known as transfer learning, which is training from the experience of solving a task or using a dataset to another similar task or dataset is the way of classification. The information collected from huge datasets, in terms of their size, is transferrable to the data that is specific to certain tasks as much as to allow the model to learn new extra data requires a minimum amount of training.

There are several reasons why pretrained models are widely used and considered beneficial: Among the most compelling arguments that underpin the increased intake and popularity of pretrained models are the following:
Feature Extraction: NMT practices are feature extracting modules which are competent in successful capture of features. Thus, the developed features can be viewed as fueling more complicated data tasks like categorizing and segmentation.
Reduced Training Time: The transfer of pretrained weights is usually a very powerful way of ensuring that the model does not have to be trained from scratch because it has been done in the conventional methods of the training of the model. This one can be highlighted in the scarcity of said resources associated with the deadline that does not allow much time to complete task.
Improved Generalization: Already trained models have new features which are used in the various fields but generally helpful in providing them with generalization concerning unseen data, say speech or image. This is also significant when developing decision criteria in various artificial intelligence activities where data sizes to accomplish a modelling task are limited.
Domain Adaptation: Pre-trained models can be re-trained on client's data and domain to adjust to small variations and differences between the source and target application context. As a consequence, the model becomes able to learn typical domain features and hence is facilitated to complete the task better.

Availability of Pretrained Models: While ready-to-use models and datasets like ImageNet for example for image classification or GloVe in natural language processing, tailored for word embeddings, are publicly available pretrained models. Having reasonable access to various applications, tasks, and trial-and-error processes for different purposes will make using this technology faster and easier.
Being aware that the pre-trained models have to be selected properly including the appropriate model architecture and pre-trained weights is necessary in such a case. Further to refinement of hyperparameters and through choosing a suitable validation type are the steps that one should consider in the pursuit of optimal performance.
Here, based on machine learning technique, pretrained image models, trained on huge image data sets, which for example, are ImageNet, can be fine-tuned using dermatoscopic images so as to enable them use their learned features for the identification and classification of skin lesions. This method of working not only positively affects the performance of the model, but it is even more effective when the given data is scanty in the medical context.

VGG16, the version "16" of the Visual Geometry Group, is an example of the convolutional neural network (CNN) model presented by the Visual Geometry Group (VGG) at the University of Oxford. As it was first presented in the paper entitled "Large-Scale Image Recognition by Very Deep Convolutional Networks" written by Karen Simonyan and Andrew Zisserman in 2014 VGG16 with its elegance and ease of use attained wide recognition within the community of image classification tasks.

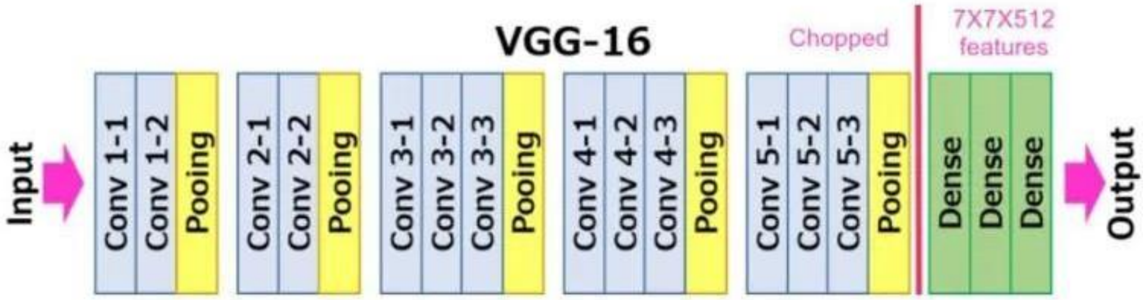


Fig 2.2

The network architecture of VGG16 only has 16 layers and that is the reason why the model is called so. This model has 13 convolutional layers and 3 fully connected layers which mainly form its structure. Convolutional layers have filters with 3x3 sizes and 1-stride which takes ReLU activation functions (ReLU) afterward. Instead of the 2x2 filters with step size of 2, we use max-pooling layers to reduce the spatial dimensions of the feature maps.

The key characteristics of VGG16 include:

Deep Architecture: VGG16 is generally famous for its deathliness, which is characterized by having 13 convolutional layers in a one below one alignment. Such depth would enable the network to get significantly variable, hierarchical features that gathered gradually from the input image.

Uniform Architecture: VGG16 architecture is as simple as skeleton has all 3x3 convolution filters and max-pooling layers located through the network. Such leveling effect serves as a simplification of the network design and development as well.

Small Filter Size: The VGG16 mini processing nodes that use 3x3 convolutional filters are specialized in multi-level feature detection which also works with low parameter count.

Pretrained Models: The pre-loaded weights developed on the Remaining Net image classification dataset originally trained for VGG16 are widely available. The pretrain models obtained these features in a way that they hardly require minimal adjustments to be used for different computer vision tasks.

Good Performance: While the structure of VGG16 is so basic, it keeps obtaining competitive results on different image classification tasks including the ILSVRC (the Large Scale Visual Recognition Challenge on ImageNet).

On the other hand, VGG16 has found its wide application as a feature extractor or a start up point model in transfer learning tasks as well. VGG16 can basically achieve a transformation to be able to adapt to different tasks by doing this: taking out fully connected layers and by replacing them with specific layers regarding the task.

MobileNet is the CNN sub-architecture that is created for mobile machines with constrained computational performance levels (i.e., mobile and embedded devices). It was introduced by Google researchers Andrew G. Howard, Menglong Zhu, Bo Chen, Dmitry Kalenichenko, Weijun Wang, Tobias Weyand, Marco Andreetto, and Hartwig Adam in their paper titled "MobileNets: The paper of 2017, " Mobile Vision Applications: Efficient Convolutional Neural Networks", is an illustration of this.

Originally designed for mobile devices, MobilNet makes a great use of the limited HRs, (memory, CPU and energy) that any device of such type can provide. As one of the most significant feature of MobileNet is its capability of identifying images accurately at relatively low cost in terms of computation and model size.

Table 1. MobileNet Body Architecture

Type / Stride	Filter Shape	Input Size
Conv / s2	$3 \times 3 \times 3 \times 32$	$224 \times 224 \times 3$
Conv dw / s1	$3 \times 3 \times 32$ dw	$112 \times 112 \times 32$
Conv / s1	$1 \times 1 \times 32 \times 64$	$112 \times 112 \times 32$
Conv dw / s2	$3 \times 3 \times 64$ dw	$112 \times 112 \times 64$
Conv / s1	$1 \times 1 \times 64 \times 128$	$56 \times 56 \times 64$
Conv dw / s1	$3 \times 3 \times 128$ dw	$56 \times 56 \times 128$
Conv / s1	$1 \times 1 \times 128 \times 128$	$56 \times 56 \times 128$
Conv dw / s2	$3 \times 3 \times 128$ dw	$56 \times 56 \times 128$
Conv / s1	$1 \times 1 \times 128 \times 256$	$28 \times 28 \times 128$
Conv dw / s1	$3 \times 3 \times 256$ dw	$28 \times 28 \times 256$
Conv / s1	$1 \times 1 \times 256 \times 256$	$28 \times 28 \times 256$
Conv dw / s2	$3 \times 3 \times 256$ dw	$28 \times 28 \times 256$
Conv / s1	$1 \times 1 \times 256 \times 512$	$14 \times 14 \times 256$
5× Conv dw / s1	$3 \times 3 \times 512$ dw	$14 \times 14 \times 512$
5× Conv / s1	$1 \times 1 \times 512 \times 512$	$14 \times 14 \times 512$
Conv dw / s2	$3 \times 3 \times 512$ dw	$14 \times 14 \times 512$
Conv / s1	$1 \times 1 \times 512 \times 1024$	$7 \times 7 \times 512$
Conv dw / s2	$3 \times 3 \times 1024$ dw	$7 \times 7 \times 1024$
Conv / s1	$1 \times 1 \times 1024 \times 1024$	$7 \times 7 \times 1024$
Avg Pool / s1	Pool 7×7	$7 \times 7 \times 1024$
FC / s1	1024×1000	$1 \times 1 \times 1024$
Softmax / s1	Classifier	$1 \times 1 \times 1000$

Fig 2.3

Here are the key characteristics of MobileNet:

Depth wise Separable Convolutions: MobileNet substitutes standard convolutional layers with depth wise separable convolution that incorporates two separate items - depth wise convolution and pointwise convolution in the place of traditional one. By doing that, separated operation constrains the number of parameters and operations, which, in turn, speeds up the process.

Depth wise Convolution: In the depth wise convolution that each input channels are filters with their own separately and it finally feature map having same number of channels as the input. This step performs a process for each channel independently by keeping spatial information in separate channels.

Pointwise Convolution: Whether it is because of culture or economic benefits offered, often a community finds it appealing to incorporate immigrants. In this way, the module is able to formulate the correlation across channel states as well as decrease the number of channels in feature maps, and therefore reduces the computational complexity.

Width Multiplier and Resolution Multiplier: Instead of conventional layers and kernels as in other CNNs, MobileNet introduces two calibrating parameters in width multiplier and resolution multiplier which let the users determine constraints on model size, computational cost, accuracy, etc. The number of channels in each layer is increased with width multiplier and alike with height multiplier. The input image size is rescaled down with resolution multiplier.

Efficient Architecture: MobileNet is also designed to strike a balance among the convolution depth, width and resolution parameters of a network along with the model size, accuracy, and computation performance by employing the depth wise separable convolutions and multipliers. This therefore makes it create as a front runner of the deployment process on constrained resources devices. MobileNet has been proven to run at high speed while being so small in size, making it applicable to image classification, object detection and semantic segmentation amongst others in the mobile image processing domain. Due to its lightweight network design and high performance, it is efficient for identifying the images and videos on devices such as smartphones, drones, and Internet-accessible devices. Furthermore, pre-trained MobileNet models are also accessible that can be used to adapt a specific task or as a feature extractor during transfer learning.

The ResNet-50 model is one of the variants of the residual network (CNN) and, hence, the name. They are the results proposed by the paper called "Deep Residual Learning for Image Recognition" written by Kaiming He, Xiangyu Zhang, Shaoqing Ren and Jian Sun from the Microsoft Research and they were published in 2015. ResNet-50 gets the + praise for its outstanding achievements in the field of image classification tasks and the fact that it is good for training of deep neural nets.

layer name	output size	18-layer	34-layer	50-layer	101-layer	152-layer
conv1	112×112	7×7, 64, stride 2				
conv2_x	56×56	3×3 max pool, stride 2				
		$\begin{bmatrix} 3\times3, 64 \\ 3\times3, 64 \end{bmatrix}\times2$	$\begin{bmatrix} 3\times3, 64 \\ 3\times3, 64 \end{bmatrix}\times3$	$\begin{bmatrix} 1\times1, 64 \\ 3\times3, 64 \\ 1\times1, 256 \end{bmatrix}\times3$	$\begin{bmatrix} 1\times1, 64 \\ 3\times3, 64 \\ 1\times1, 256 \end{bmatrix}\times3$	$\begin{bmatrix} 1\times1, 64 \\ 3\times3, 64 \\ 1\times1, 256 \end{bmatrix}\times3$
conv3_x	28×28	$\begin{bmatrix} 3\times3, 128 \\ 3\times3, 128 \end{bmatrix}\times2$	$\begin{bmatrix} 3\times3, 128 \\ 3\times3, 128 \end{bmatrix}\times4$	$\begin{bmatrix} 1\times1, 128 \\ 3\times3, 128 \\ 1\times1, 512 \end{bmatrix}\times4$	$\begin{bmatrix} 1\times1, 128 \\ 3\times3, 128 \\ 1\times1, 512 \end{bmatrix}\times4$	$\begin{bmatrix} 1\times1, 128 \\ 3\times3, 128 \\ 1\times1, 512 \end{bmatrix}\times8$
conv4_x	14×14	$\begin{bmatrix} 3\times3, 256 \\ 3\times3, 256 \end{bmatrix}\times2$	$\begin{bmatrix} 3\times3, 256 \\ 3\times3, 256 \end{bmatrix}\times6$	$\begin{bmatrix} 1\times1, 256 \\ 3\times3, 256 \\ 1\times1, 1024 \end{bmatrix}\times6$	$\begin{bmatrix} 1\times1, 256 \\ 3\times3, 256 \\ 1\times1, 1024 \end{bmatrix}\times23$	$\begin{bmatrix} 1\times1, 256 \\ 3\times3, 256 \\ 1\times1, 1024 \end{bmatrix}\times36$
conv5_x	7×7	$\begin{bmatrix} 3\times3, 512 \\ 3\times3, 512 \end{bmatrix}\times2$	$\begin{bmatrix} 3\times3, 512 \\ 3\times3, 512 \end{bmatrix}\times3$	$\begin{bmatrix} 1\times1, 512 \\ 3\times3, 512 \\ 1\times1, 2048 \end{bmatrix}\times3$	$\begin{bmatrix} 1\times1, 512 \\ 3\times3, 512 \\ 1\times1, 2048 \end{bmatrix}\times3$	$\begin{bmatrix} 1\times1, 512 \\ 3\times3, 512 \\ 1\times1, 2048 \end{bmatrix}\times3$
	1×1	average pool, 1000-d fc, softmax				
FLOPs		1.8×10^9	3.6×10^9	3.8×10^9	7.6×10^9	11.3×10^9

Fig 2.4

Here are the key features of ResNet-50:

Deep Architecture: ResNet-50 is a deep neural network having layers which are in the range of 50 layers. Unlike the predecessors, such as VGG-16 and VGG-19, it is deeper and more precisely enabling for complex pattern and features recognition in input images.

Residual Connections: ResNet-50's one key feature is the skip connection in combination with residual mapping, also known as the useful skip connection in this neural network. The connections in these networks correspond to the residual learning of the functions involved instead of painfully trying to get the underlying mapping directly. In Residual connections, error signal from a layer is transferred to the previous layers that may escape vanishing gradient problem occurring in training very deep networks, allowing ResNet-50 to effectively train hundreds of layers.

Bottleneck Architecture: ResNet-50 introduces bottle neck structure by the deeper layers of the network which tries to enhance complexity of the computations. It is implemented with a sequential structure by using 1x1, 3x3 and 1x1 convolutional layers, where the 1x1 convolutions are meant to reduce the dimensions of the initial features and then to increase them again, and the main extraction function is performed by the 3x3 convolution layer.

Pretrained models: Pretrained versions of ResNet-50 trained on large-scale image datasets, such as

ImageNet, are readily available. They are already trained on millions of images. They can be fine-tuned on new data to be used as feature extractors in a computer vision model for image classification, object detection, and semantic segmentation among other. Using pretrained models usually results in faster convergence and better generalization performance, especially on small target datasets.

Applications: The ResNet-50 is widely applied to numerous computer vision problems like image classification, object detection, image segmentation, and generation. It has proven its performance on very deep networks and has been the go-to solution in both research and production.

The ***DenseNet-121*** introduced by Gao Huang, Zhuang Liu, Laurens van der Maaten, and Kilian Q. Weinberger with the article “Densely Connected Convolutional Networks” in 2017 is a convolutional neural network architecture. DenseNet-121 is a member of the DenseNet family, which stands out with its unique dense connections between layers, allowing for parameter efficiency..

Layers	Output Size	DenseNet-121	DenseNet-169	DenseNet-201	DenseNet-264
Convolution	112×112	7×7 conv, stride 2			
Pooling	56×56	3×3 max pool, stride 2			
Dense Block (1)	56×56	$\begin{bmatrix} 1 \times 1 \text{ conv} \\ 3 \times 3 \text{ conv} \end{bmatrix} \times 6$	$\begin{bmatrix} 1 \times 1 \text{ conv} \\ 3 \times 3 \text{ conv} \end{bmatrix} \times 6$	$\begin{bmatrix} 1 \times 1 \text{ conv} \\ 3 \times 3 \text{ conv} \end{bmatrix} \times 6$	$\begin{bmatrix} 1 \times 1 \text{ conv} \\ 3 \times 3 \text{ conv} \end{bmatrix} \times 6$
Transition Layer (1)	56×56	1×1 conv			
	28×28	2×2 average pool, stride 2			
Dense Block (2)	28×28	$\begin{bmatrix} 1 \times 1 \text{ conv} \\ 3 \times 3 \text{ conv} \end{bmatrix} \times 12$	$\begin{bmatrix} 1 \times 1 \text{ conv} \\ 3 \times 3 \text{ conv} \end{bmatrix} \times 12$	$\begin{bmatrix} 1 \times 1 \text{ conv} \\ 3 \times 3 \text{ conv} \end{bmatrix} \times 12$	$\begin{bmatrix} 1 \times 1 \text{ conv} \\ 3 \times 3 \text{ conv} \end{bmatrix} \times 12$
Transition Layer (2)	28×28	1×1 conv			
	14×14	2×2 average pool, stride 2			
Dense Block (3)	14×14	$\begin{bmatrix} 1 \times 1 \text{ conv} \\ 3 \times 3 \text{ conv} \end{bmatrix} \times 24$	$\begin{bmatrix} 1 \times 1 \text{ conv} \\ 3 \times 3 \text{ conv} \end{bmatrix} \times 32$	$\begin{bmatrix} 1 \times 1 \text{ conv} \\ 3 \times 3 \text{ conv} \end{bmatrix} \times 48$	$\begin{bmatrix} 1 \times 1 \text{ conv} \\ 3 \times 3 \text{ conv} \end{bmatrix} \times 64$
Transition Layer (3)	14×14	1×1 conv			
	7×7	2×2 average pool, stride 2			
Dense Block (4)	7×7	$\begin{bmatrix} 1 \times 1 \text{ conv} \\ 3 \times 3 \text{ conv} \end{bmatrix} \times 16$	$\begin{bmatrix} 1 \times 1 \text{ conv} \\ 3 \times 3 \text{ conv} \end{bmatrix} \times 32$	$\begin{bmatrix} 1 \times 1 \text{ conv} \\ 3 \times 3 \text{ conv} \end{bmatrix} \times 32$	$\begin{bmatrix} 1 \times 1 \text{ conv} \\ 3 \times 3 \text{ conv} \end{bmatrix} \times 48$
Classification Layer	1×1	7×7 global average pool			
		1000D fully-connected, softmax			

Fig2.5

Here are the key features of DenseNet-121:

Dense Connectivity: The network is highly connected and each layer operates as a feed-forward unit which is connected to every other layer. Different from CNN that are based on sequential connection of the layers, DenseNet uses connections within the dense block for each layer. Dense connectivity promotes attribute sharing, signal flow and to contrast, avoids vanishing gradient problem. High interconnectivity in the network not only facilitates the deeper propagation of features, but also enable a robust network to be created that can identify more discriminating features.

Bottleneck Layers: As ResNet does, DenseNet-121 is designed with the use of the bottleneck layers that are aimed at the complexities reduction. In these bottleneck layers, the 1x1 convolutional layer with 3x3 convolutional layer precedes. The 1x1 convolutions take in the compression to eliminate and later reconstruct the number of feature maps, and it occurs in this way that the flow of the information is squeezed and the cost of computer processing is lower.

Transition Layers: The transitional layers used between dense blocks by DenseNet-121 controls the number of feature map and, this way, the number of parameters required by the network is reduced, too. Generally, the transition layers are composed of a sequence of operations including, layer norm, 1x1 convolution followed by 2x2 average (avg) pooling - all of which are done consecutively. This

layers' role aimed at retaining the spatial compactness of the network and as a consequence, to avoid overfitting.
Feature Concatenation: Feature map of one neural layer in DensNet is combined and stacked into the next layer with a dense block. This concatenation becomes the main way the layers can now talk to each other directly, and share information. Through concatenated features rather than adding them, DenseNet keeps all layers' information and thus overcomplete. This results in more accurate feature presentation.
Efficient Parameter Usage: DenseNet-121 deserves attention because it performs well with relatively smaller number of parameters compared to other type of CNN network block constructions. The location of the “dense" pattern of connections allows the network to use the parameters consequently, efficient, and learn more complex and distinct knowledge representations.
Applications: DenseNet-121 has been widely used for different computer vision applications such as image classification, object detection, semantic segmentation, Medical image analysis, etc. Its ability to use parameters in an efficient way and higher prevision make it suitable for lab and public use.

In short, Dense-Net-121's dense connection architecture and good parameters utilize feature makes it a very powerful CNN architecture for image analysis tasks. It provides very detailed representations of features by means of denser connections and also has a remarkable small model size compared to many models making it highly admired by the deep learning community.

2.5 Evolution of Diagnostic Technologies in Dermatology:

The technological development in dermatology has witnessed a unique transformation of previously complicated excellence, to simpler and accurate disease diagnosing methods that make skin disease diagnosis more effective and accessible to everyone. In time, the appearance of a spectrum of diagnostic tools and methodologies which has helped to increase the level of clinical knowledge regarding of skin disorders and eventually improve the medical outcomes.
Visual Inspection: Manual visual diagnosis has been the leading factor in the dermatological diagnosis for a very long period of time. The dermatological specialists trust their skills as well as visual assessment of the skin lesion to detect any which is characterize, and also make their diagnostic analysis. Traditionally visual check process is the chief in the inspection process but latest technologies has helped in the improvement and the methodical analysis of images taken.
Dermatoscopy: Dermatoscopy is the term used to describe dermoscopy and epiluminescence microscopy. These are non-invasive imaging techniques that allow the complete and magnified visualization of skin lesions. Through emitting polarized or non-polarized light on the skin and using a commercial handheld dermoscope, a physician can minutely examine the microstructures and pigmentation skin lesion. The use of dermatoscopy improves the diagnostic capabilities of melanoma and other skin cancers because, in addition to providing information about the structure and blood vessel configuration of affected skin, it also detects signs not otherwise visible to the naked eye such as color variations.
Reflectance Confocal Microscopy (RCM): Cell depictive spatial change is also possible with this advanced imaging technique where real time development of skin structures is visualized at cellular level. RCM exploits the laser light to penetrate the skin and to capture the high-resolution images of the cellular and the tissue structures without undergoing biopsy unless it is necessary. The beauty of this tech is the precision in which it allows dermatologists to examine cellular morphology specifically those more complicated slight architectural changes linked with skin cancer and inflammatory skin diseases.

Optical Coherence Tomography (OCT): Visual light coherence tomography is a noninvasive imaging which uses low-coherence light to make cross-sectional images out of tissue microstructure. OCT gives high resolution real time images of skin layers and structures , thus, measurement of epidermal thickness, dermal-epidermal junction and presence of inflammatory cells can be done. Dermatologists can use OCT for diagnostic and therapeutic purposes in such conditions as skin cancer and psoriasis.

Artificial Intelligence and Machine Learning: The recent breakthroughs in artificial intelligence (AI) and machine learning have transformed dermatological diagnosis thanks to machine learning algorithms being able to perceive dermatoscopic images and clinical data in such a detailed and accurate manner. Deep learning technologies, especially the CNNs (ConvNets), are able to teach an algorithm to recognize the patterns and features doing signs of various skin problems and to get the accuracy of an expert dermatologist. AI-based diagnostics are instrumental in enhancing diagnostic rationality, reducing the occurrence of diagnostic mistakes and availing specialist services to dermatology patients, particularly in areas with deficient health facilities.

Advancements in Deep Learning for Medical Imaging

The emergence of diagnostic technology in dermatology has experienced changes in substantial stage to make the field of skin diseases diagnosis accurately, in fun and fast way. Over the past periods the multiple diagnostic tools and different techniques have come into existence, which not only plays a role of promoting our knowledge regarding skin diseases but also help in the improvement of providing the patient care.

Visual Inspection: Visual inspection which is the fundamental tool of dermatologic diagnosis has been used since times immemorial throughout history. Skin lesions in dermatology are typically identified and characterized through the dermatologist’s specialist knowledge and visual examination. The dermatologist then makes a diagnosis by giving consideration to all the necessary factors. The visual inspection still exists although it is complemented and even made better using the tech a

Artificial Intelligence and Machine Learning: Faster and more accurate diagnosis in dermatology is now more possible thanks to the panoply of artificial intelligence technologies and the advent of machine learning that allows the automated analysis of the dermatoscopic images and the clinical data. The deep learning algorithms, particularly the convolutional neural networks (CNN), are able to extract patterns and features that would otherwise be hard to see for the less trained eye, and equivalent to the dermatologists diagnosis. AI-powered diagnostic tools are able to improve diagnostic effectiveness, minimize errors in diagnosis and expand dermatology healthcare even to far places that previously were not served well due to lack of appropriate resources.

In general, we observe a change from invasive technologies to non-invasive imaging methods, the improvement of diagnostic accuracy and usability of the images with advanced techniques, and a rise in the implementation of artificial intelligence (AI) for automated data analysis and interpretation. These new achievements hold great expectancy in the sphere of timely diagnostics, individualized treatment and improved patients' conditions in the field of dermatology.

CHAPTER 3: METHODOLOGY

3.1 Data Collection and Description:

To carry out our research, we utilized the HAM10000 dataset (Human Against Machine), which comprises 10,015 dermatoscopic images classified into seven distinct categories: actinic keratosis (akiec) portraying a total of 327 images, basal cell carcinoma (bcc) showing 541 images, benign keratosis (bkl) with 1099 images, dermatofibroma (df) presenting 155 images, melanocytic nevi (nv) displaying 670 They highlight the different skin lesions

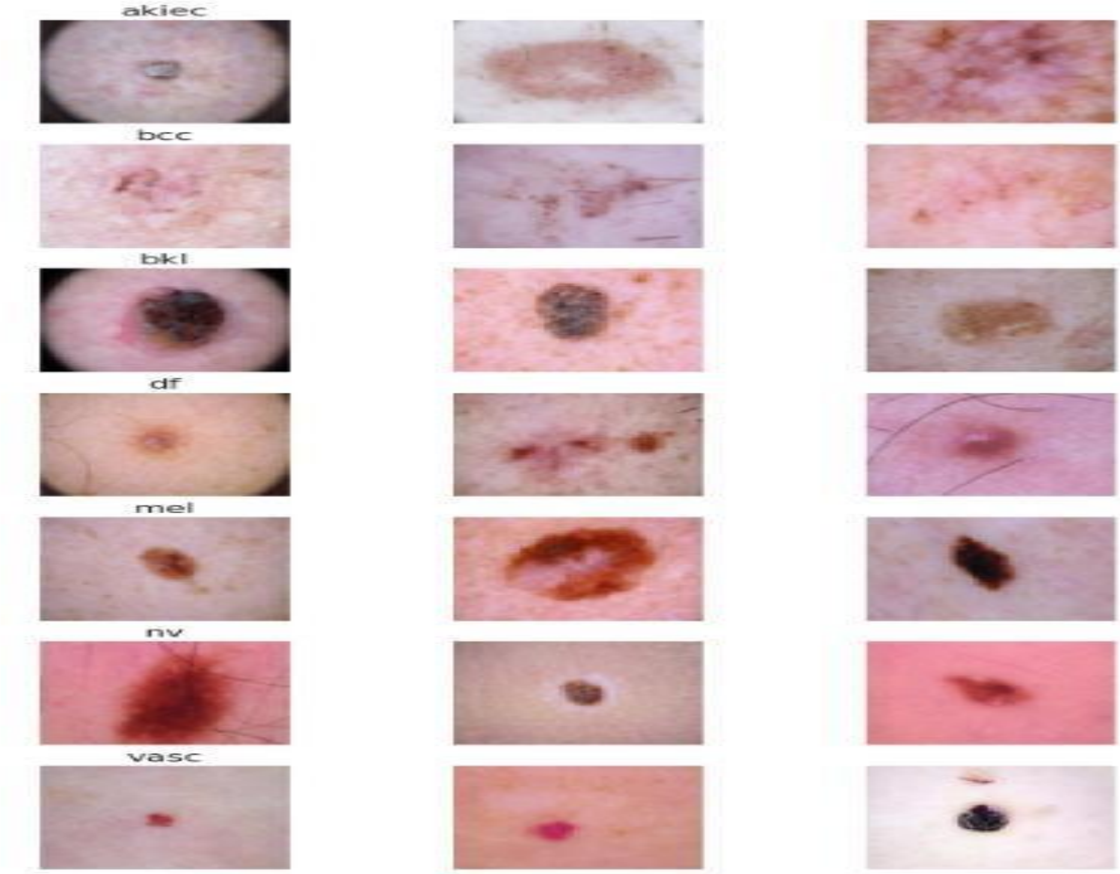


Fig 3.1

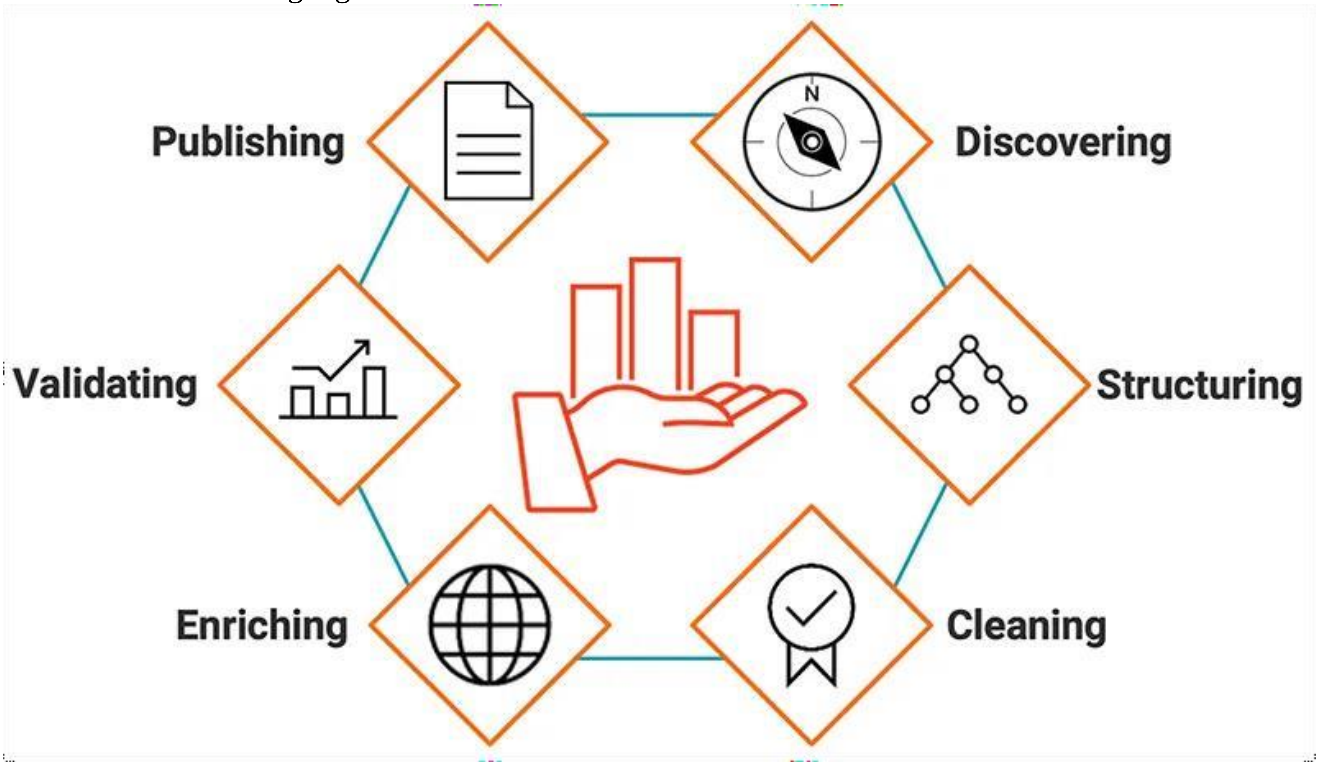
The training set of HAM10000 comprises pigmented lesions that represent a variety of population. The specific Austrian lesions compose the whole population of patients, consecutively referred to a tertiary European center, which is dedicated to melanoma detection during an early phase, with a high prevalence of nevi and a history of melanoma. As opposed, the Australian group deals with the groups of lesions obtained from the patients that live in the area of Australia with high skin cancer morbidity, and usually severe chronic sun damage. Unquestionably, as chronically sun-damaged skin manifests as multiple solar lentigines and angiomas, in combination with ectatic vessels, and occasional lesions of the seborrheic keratosa, this corresponds almost fully with actual clinical appearance. In each site, the dermatoscopic images have been taken using various apparatus, involving polarized and non-polarized dermatoscopy, in order to demonstrate the variety of pigmented skin lesions, which are clinically significant.

The dataset summarizes practically all cases of pigmented skin lesions that are often encountered at dermatological clinics with more than 95% of those being categorized as one of the 7 diagnostic categories. However, it is critical increasingly to categorize abnormalities as malignant vs benign, as they are largely meant to help determine the treatment plan and guidelines. Each diagnostic group including actinic keratosis (akiec) , basal cell carcinoma (bcc) , benign keratosis (bkl) , dermatofibroma (df) , melanocytic nevi (nv) , melanoma (mel) , and vascular skin lesions (vasc) offers specific dermatoscopic and clinical features. An example is Actinic Keratoses which often appear as crusty patches induced by UV rays, while the BCC may have other variants such as flat ones, nodules, pigmented or cysts. Also, benign keratosis extends to such cubic keratoses, seborrheic keratoses, and solar lentigines; some conditions that have biological correlations and histopathological similarities appear, simultaneously.

HAM10000 database is a good system for help training and testing of machine learning models for skin lesion classification which provide a typical output of the disease pictured by dermatoscopic images.

3.2 Data Preprocessing

Data preprocessing, like label encoding, is an essential element in any machine learning project, especially in such confusing cases as categorical data, for instance, the type of skin lesion in our dataset. Categorical encoding is a representation of categorical labels with digital values that are used in the machine learning algorithms.



3.2

The data preprocessing pipeline for our skin cancer classification project structured by stages, with label encoding, one of the essential parts. undefined

Data Understanding: Before the actual preprocessing, the knowledge of the data set structure and its dependency on data is a must. Our cases involve HAM10000, which is the image dataset available with dermatoscopic pictures of the skin lesions characterized into 7 different categories.

Handling Categorical Labels: The types of skin lesions described in the dataset were considered categorical variables, however, in order to be processed by machine learning algorithms, they needed to be converted into numeric format. Transformation of the qualitative data into a digestible format was achieved using the label encoding method.

Label Encoding Process: Using the Label Encoder class from scikit-learn, we brought a category label encoding into play. This process was about allocating the value of one such numerical to each category. Likewise, the digits may comprise 0 for "actinic keratosis", 1 for "basal cell carcinoma" and so on.

Impact on Data: In terms of the labels, one of the biggest changes that the label encoding produced was the conversion from the categorical labels to the numerical representation. This transformation was of seminal import as it enabled machine learning algorithms to not only analyze but also process the data accordingly. Having labels encoded thus helped us get rid of the algorithms' direct reliance

on the mechanisms to understand textual and categorized data, making our set smoother similar to all machine learning methods.
Facilitating Model Training: Preprocessed data, which also contains the one-hot encoded labels, were the inputs of machine learning models designed for classification problem. With the operation process of machine learning algorithms being based on a numerical data format, label encoding made sure that the models would have the necessary skills to learn from the dataset and optimize the outputs.
Over all end, through the process of label encoding, data preprocessing has had a remarkable though outstanding impact on ensuring the skin lesion dataset is ready to be utilized for machine learning tasks. Through the usage of categorical-label-to-numerical-representations, we could ensure the proper computability of the data by the machine learning algorithms, and that helped us to train accurate models for skin cancer classification.

3.2.1 Image Resizing and Normalization

The image resizing and normalization in our "skin cancer classification project" played very important roles in achieving better model performance and reduced processing time.

Image Resizing:
The model of ours was fed with training images having 65x65 pixels for each channel in RGB format. But, this original dataset of images may be of varied sizes.
We have coded in image processing libraries like OpenCV and PIL (Python Imaging Library) to resize all input images into the model architecture dimensions to maintain consistency and compatibility.
among which was compressing the files to a more manageable size. Accordingly, it lowered the job of model training and inference by reducing the computational load during implementation. The small images of pins require less memory and speed up training process on the larger datasets due to less resources they require. Furthermore, small images did not consume high memory space, thus quicker data loading, augmentation, and processing were enabled, with that, the entire phase of model development becomes faster.

Normalization:
Normalization is a part of the standard preprocessing process where input image pixel values are scaled to a predefined range, for instance between 0 and 1 or -1 and 1.
Within our project, the normalization of pixel values of all resized images is achieved. What followed was a division of the pixel values by 255, the number that the average 8-bit pixel can receive, so that all pixel values are among [0, 1].
Stabilization and the process of fasting is possible with normalization, operating on comparable ranges by the
feature scale of data input. It precludes others features overpowering the others during training and it facilitates the optimization algorithm to converge much faster to an optimum solution.
Furthermore, the normalization procedure can help in improving the numerical stability of the training process which may often be a great factor of the model performance on unseen data and generalization.
Eventually, image resizing and normalization process were instrumental in preprocessing the data so that our system could end up with enough data to train the classifier to detect skin cancer. By shrinking the sizes of all the images to a common dimension setting and adjusting their values to

come to the ordinary values, we gained efficiency, stability, and effectiveness of the model training process and in the long run outputs more accurate previsions and a better generalization with unseen images.

3.2.2 Data augmentation

Data augmentation, as a technique, provides additional data that serves to improve the variety and resiliency of datasets mainly in computer vision tasks which include image classification. Through rotations, tears, flips, brightness variations, and other modifications of the original data, supplement techniques create more image trainings sets. These artificially enlarged samples arm the model with a wider range of variations and teach it to classify the invariant features, which enhance generalization to new data and evaluation of the model.
Besides our skin cancer classification project, the greatest challenge in my opinion is the excessive database inequality. On instances where some classes organizes more samples than others this means traditional data augmentation is not adequate; it was therefore necessary to come up with better ways of achieving the balance. Although an increase in the sample size of the minority class can equalize the representativeness of the dataset, it might not be accurate after all the progress because of an imbalanced prediction.

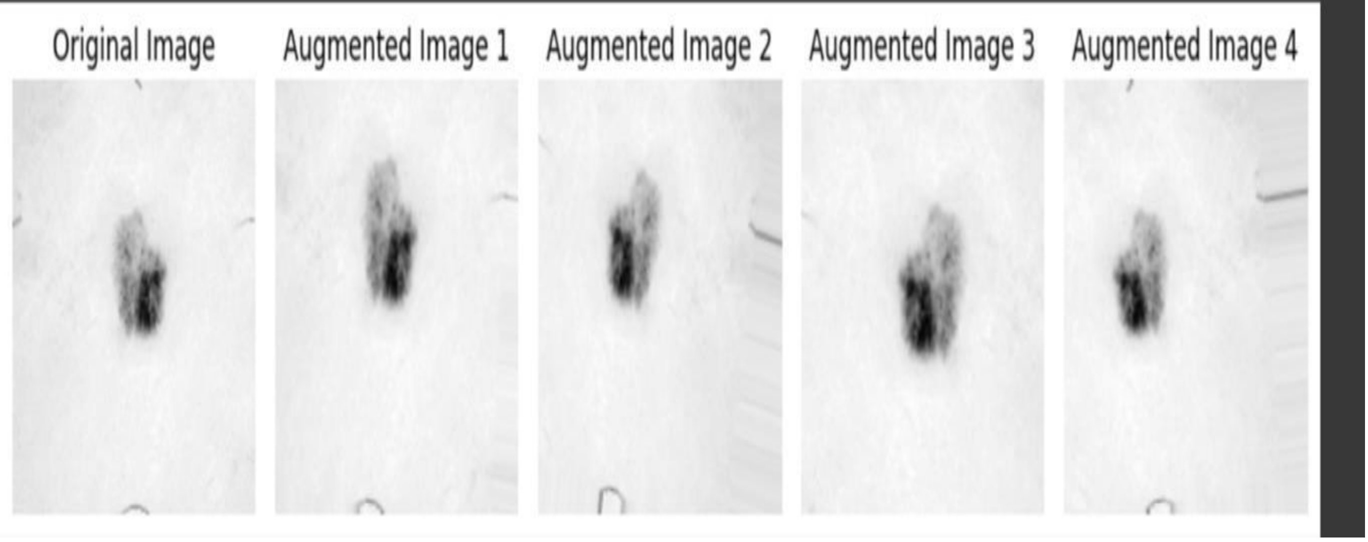


Fig.34

At the end, we used methods like oversampling which helped to stifle the effect of the class imbalances on the outcome of the decisions. Resampling methods imply the rearrangement of the dataset's class distribution, done via the oversampling of minority class samples, under sampling of majority class samples, or a mix of both. Data augmentation aims at creating synthetic variations of the existing data by applying different techniques on the dataset. On the other hand, resampling shuffles the entire dataset thus contributing to better classes representation and balance.
In the case of ours, resampling was a more efficient way to cope with class imbalances and to develop our model capabilities on minority classes. As a result of this technique, the model was given samples that were duplicated or removed strategically, creating a dataset that was better balanced across all the classes. This allowed the model to learn from a set of examples which represented the entirety of the data. While data augmentation will continue to be a useful method for improving the diversity of datasets and the robustness of models, it may not truly work well against highly imbalanced datasets. Balanced resampling may be more targeted and better suited to address class imbalance and model

performance.

3.2.3 Balancing the Dataset

Balancing the dataset becomes a crucial part of machine learning, approximately completed when working with a dataset with imbalance where children classes are deficient in comparison with some others. In this context, class imbalance is dealt multiple ways, which have routine drawbacks and perks.

The other tactic is ***under sampling*** where the primary class objects are randomly deleted such that a better distribution class population is built. Whilst the creation of an imbalanced class under-representation is an effective method for removing any unnecessary information from the majority class, there is a danger of losing potentially valuable data from the minority class.

Sampling can be done, though, by repeating the occurrences of the minority class to be equal to the majority class size. Create an AI chatbot using pre-trained models or with your custom-trained language models to understand customers' queries and provide accurate and relevant information. This is done by offering more training data with the minority class which shows ups in representation of the class in the training data. On the other hand, although sampling upweights the minority class, it may result in overfitting that occurs during a training procedure, where the model learns to memorize the repeated samples instead of identifying the real patterns.

The Synthetic Minority Over-sampling Technique (SMOTE), which is a popular oversampling technique, increases the synthetic samples for the minority class by taking a point in-between existing instances within the feature space. SMOTE supposes the assumption that it tends to reduce the risk of overfitting in that it does generate new samples that do have a resemblance, however they are not copies of the original instances of the minority class.

In this investigation of skin cancer, we chose resampling as the major balancing technique as it is very crucial and very simple method, especially in this image context. Resampling is the process of carefully choosing from the majority class, and balancing it with the minority class which results in a more fair representation of the data. Different to data augmentation, in which occur shifts in data features of initial samples, the resampling changes the distribution of dataset composition by adjusting class frequencies.

Through a specified skewing of the dataset's class distribution , resampling intends to give the model enough exposure to all the classes, hence removing the risk of bias towards the majority class. It reduces complexity of preprocessing pipeline, particularly in the case of image data, where distinct augmentation of individual samples may not be so easy and straightforward. Ultimately, resampling provides a useful and convenient tool for balancing imbalanced datasets, contributing to more robust model training and fewer chances of errors.

3.3 Model Architecture Selection

Model architecture selection is the single most influential part while creating a machine learning system as it not only affects the system speed, but also the interpretability of the model, i.e., the level to which the model is transparent to its users. In skin cancer segmentation, choosing the right architecture means you have to take into account the complexity of the subject, resources available, and accuracy balance with productivity.

In image classification tasks principally applied, the CNN (Convolutional Neural Network) is a common type of architecture. CNNs, however, are remarkable in their capabilities when it comes to

image recognition tasks because of their peculiar habit to self-learn abstract layers directly from the data. That framework is composed of many layers, such as the convolving layer, the pooling layer and the fully-connected layer. Different parts of the image are analyzed and presented as a result.
Within the scope of the skin cancer project's classification, an implementation of a Deep Convolutional Neural Network (DCNN) architecture was made use of. DCNN are CNN kind of modification with more intricate layers structure continuing from numerous convolutional and pooling layers with finally fully connected layers. This hierarchical structure enables the network to explore deeper into the input images, and thus be able to perceive more sophisticated patterns and activities, which provided with a possibility to classify the input images more accurately.
The DCNN design adopted by our project consists of several convolutional layers with stepwise complexity. Each layer is competent in the feature recognition at various levels of abstraction. They usually are proceeded by the pooling layers which reduce the computational complexity of the network and improve its translational invariance by the down sampling of the feature maps.
Following the convolutional and pooling layers, the DCNN typically has one or more fully connected layers; they combine the extracted traits and vector them to the output classes. Some of the layers are fully connected layers which are responsible for making the final decision after the computations are done over the features from the first level of layers.
Besides, enhance generalization by means of dropout regularization and batch normalization methods that are added into our DCNN structure as well. Irregular dropout kills with probabilities some of the units during the training, and as a result the network becomes able to learn more robust characteristics. Batch normalization helps to reduce the internal covariate shift by converting the activations of each layer to a standardized distribution and by speeding up the training process.
Consequently, the chosen DCNN architecture is capable of combining the hierarchical features learning capabilities inherent in deep learning models and classifying the skin lesions dermatoscopic images into different categories. Through meticulous modeling and fine tuning, we seek to maximize the model's accuracy rate, and guarantee the optimal performance while considering computational efficiency and scalability.

3.3.1 Convolutional Neural Network Design

The Convolutional Neural Network (CNN) is conceptualized as a type of deep neural network that is specifically designed for vision-related data, like images. CNNs made learning of patterns in different visual features, from an autonomous data, without the niches of pre-scripted manual extraction possible.
CNN trajectory can be summarized at its core, by observing that, it consists of several layers and each layer is made for applying specific function on the data (input). The central elements of a convolutional neural network (CNN) constitute the convolutional layer, pooling layer, and fully connected layers.

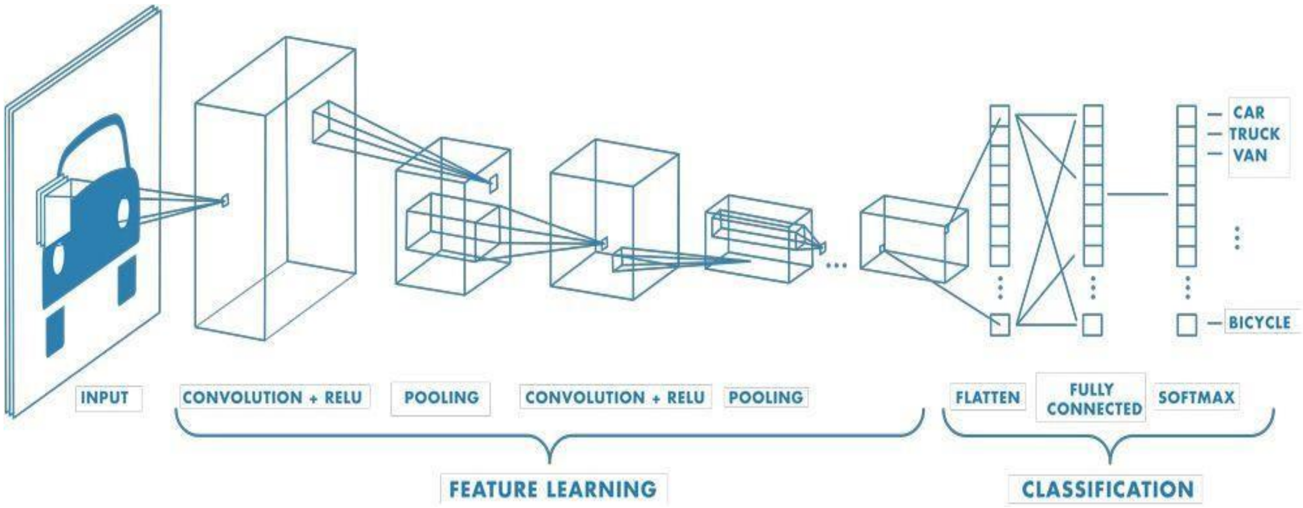


Fig 3.5

Convolutional Layers: It is the base of CNN architecture, that is most important to spell out the features from the input image. In a convolutional layer, a filter set consisting of learnable filters (normally called kernels) is applied to the input image with certain strides. The sliding window technique comes to the fore in this scanning approach. Each filter detects specific patterns/form, e.g. contours, texture, or shapes or any other feature. The network prunes these weights during the training process of the process of backpropagation, with an aim best values.

Pooling Layers: Through the use of pooling, layers you compress or reduce, the map of the features that are produced by convolutional layers. The max pooling operation (a common one) includes the identification of the maximum value within each local area of the feature map. Pooling assists in shrinking the spatial dimensions of the feature maps , retaining the most useful data that leads to the networks becoming more computation-efficient and reduce the chances of overfitting.

Fully Connected Layers: On the other hand, convolutional and pooling layers are followed by a flattening of feature maps, which is then going through one or more fully connected layers. One the top of that, these layers act as simple feed-forward networks, where all neurons are connected to neurons from the previous layer. These completely connected layers perform high-level representation of features as well as mapping the learned attributes to the respective output classes.

Further than these central features, CNNs typically inject other methods to lift performance and boost efficiency. Among them, the functions of activation (like ReLU), batch normalization, regularization with dropout and up-to-date optimization (including Adam or RMSprop) are to be mentioned.

The training procedure of a CNN is by feeding input picture to the network, predicting the output, comparing it with the ground truth labels, and then adjusting the network parameters (weights and biases) in order to reduce the loss or prediction error through the process of backpropagation. While following this process, the algorithm is iterated across many epochs until it finally converges to find the best settings of parameters.

There is no doubt CNNs are accomplishing quite impressive results for a whole variety of computer vision problems, including image classification, object detection, and image segmentation. They are efficient at capturing hierarchical features from unfiltered pixels in a manner that is critical for useful contextual insights.

3.3.2 Transfer Learning Approach

Transfer learning is a machine learning process where a model trained in one task is turned to be used

in a new application with a related task. Hence, instead of reconstruction of the learning process since the beginning, use the received knowledge from one problem to another and then apply the knowledge to a problem but similar to the previous one.
In the case of deep learning, transfer learning was defined as using networks that have been previously trained on huge datasets, which are applied to tasks like image classification and most frequently have large image datasets like ImageNet. These models which have been pre-trained can generalize to convey meaningful features from raw data and to capture general patterns that are useful for a broad set of activities.

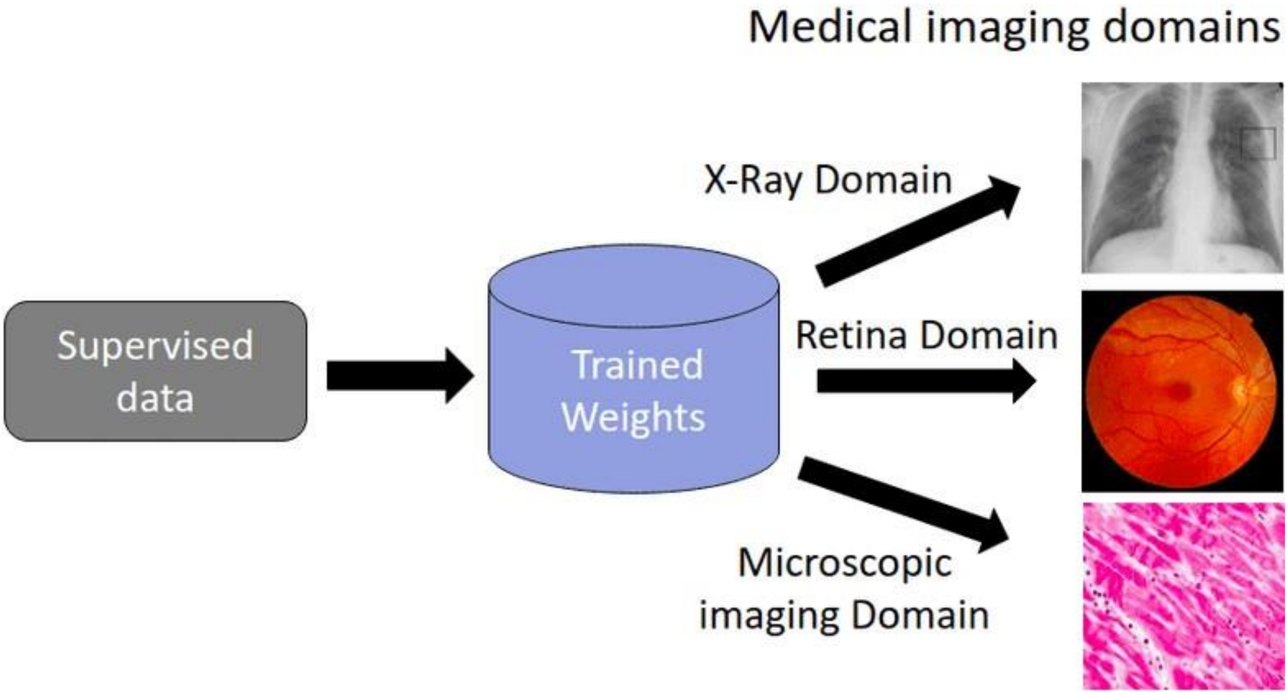


Fig 3.6

Transfer learning is particularly useful in situations where:

Limited Data: Transfer learning is a concept that makes it possible to exploit the understanding that is learned from a big corpus of related data so as to enhance the performance of the model when you have just a small dataset available.
Computation and Time Constraints: Scratch training deep neural networks can be a big consumption of resources both in terms of computational power and the time it takes. Given that the pre-trained models remain at the basis of your development, which is a common practice, you can save a great amount of time and expenses that are required to train a model manually.
Domain Adaptation: Because transfer learning is orientation to the model which already trained to the data from the one domain and being able to be adapted to another domain. For instance, a model that differentiates one kind of objects can be re-trained to recognize the duplicate objects despite of that they are taken from a separate domain.
In our project, we used transfer learning on the basis of pre-trained CNN architectures like VGG16 and VGG19 to give the desired results. These models were initially trained on datasets like ImageNet, which contain vast amounts of visual sample data. They then have to learn how to recognize a wide spectrum of patterns. Through a utilization of these bag-of-words pre-trained models, the starting process for our skin cancer classification task was speeded and this situation was enabled.

We used transfer learning by selecting the panoptic CNN models already pre-trained from the domain of dermatoscopy and improved them specifically for our dataset of dermatoscopy images. This comprised of altering the last layers of the already-pretrained networks to have the same number of classes and fine-tuning the network on our data by taking a second pass. Through this we were able to modify the pre-trained models, enabling us to put them on tune with the skin cancer classifier task we used, reaching a higher accuracy than starting from scratch might have, that's because of our dataset which happens to be small.
However, the transfer learning proved to be a significant factor in our project because it gave us the ability to utilize the representational power of PRED-trained models and then make them suitable for our job. These changes finally brought about higher performance and faster convergence during the training process.

3.4 Training Setup and Hyperparameter Tuning

Training setup and hyperparameter tuning are critical aspects of developing an effective machine learning model. When training a model, various parameters, known as hyperparameters, need to be configured to optimize performance. Hyperparameters control the learning process and directly impact the model's ability to generalize well to new, unseen data.
Hyperparameter tuning involves systematically adjusting these parameters to find the optimal combination that maximizes the model's performance metrics, such as accuracy, precision, or recall. Common hyperparameters include learning rate, batch size, number of epochs, optimizer choice, and network architecture parameters.

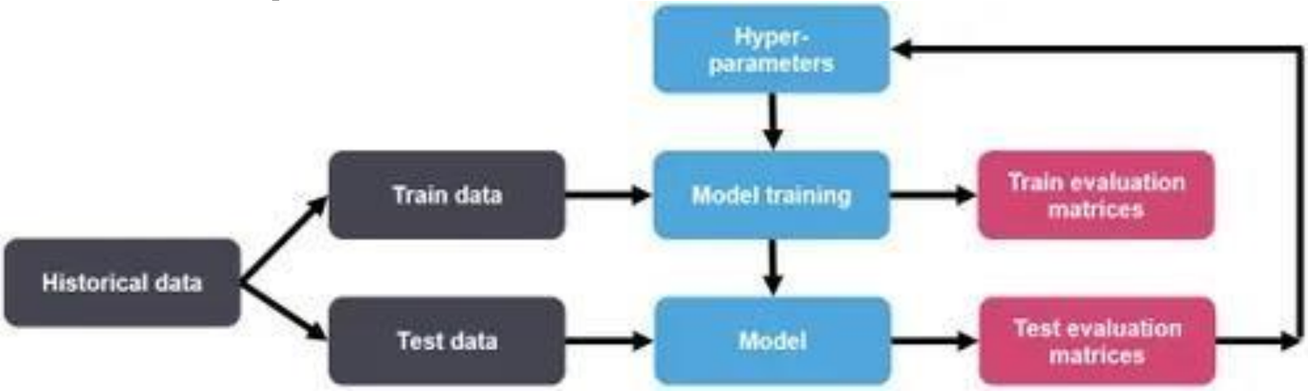


Fig 3.7

The training setup encompasses the entire process of preparing the data, defining the model architecture, selecting appropriate hyperparameters, and executing the training process.
It involves several key steps:

Data Preparation: This involves preprocessing the data, such as resizing images, normalization, and splitting the dataset into training, validation, and testing sets. Proper data preprocessing ensures that the model can effectively learn from the data and generalize well to unseen samples.
Model Architecture Definition: The wrong architecture for the neural network can lead to problems in the performance of the network. Choosing the right architecture varies depending on the problem domain and the form data takes. A CNN might be a suitable architecture for image and video input data, while RNN and hybrid models may be appropriate for time or linguistic data. The lack of standardization among the various AI solutions complicates their comparison. The model architecture discerns how the neural network layers are arranged and connected to work with the input data and get the right prediction.

Hyperparameter Selection: The choice of hyperparameters has a great impact on training trajectory and success of a model. Discerning the right values of the hyperparameters can be a difficult task, sometimes demanding for experimentation and adjustments. A variety of methods include grid search, random search, or Bayesian optimization, among other ones, that enable searching through the entire range of hyperparameters with the goal of defining the optimal configuration.

Training Process: Training the model is done by the training data and optimization algorithm (e.g. gradient descent) and the selected hyperparameters guides the model to find the best fit parameters. Conceptually, the training process is about cumulatively exposing a batch of the data to the network, driving a loss function, and optimizing the parameters of the model to work toward minimizing the loss function.

Validation and Evaluation: In the course of training process, it is a necessity to keep the check of the model's performance on independent validation set not to allow it to get overfitted. The above parameters are updated against the validation score metrics, finally after which the final trained model is evaluated on the test set in order to judge its generalization capability

Hyperparameter tuning seeks to achieve a balance given model complexity and generalization behavior. Through the uniform highlighting of the parameters, the practitioners can perfect their models applying the best hyperparameters configuration to achieve the optimal performance for the specified task.

CHAPTER 4: EXPERIMENTAL RESULTS

The series of experiments to evaluate the performance of our model generated a predictive model for the evaluation of the skin cancer lesions. In the next paragraph, we present an in-depth description of the techniques and their related outcomes.

First, we set our input image size to 65x65 and 3 color channels (RGB) as our standard. This step of preprocessing achieved uniformity that enables a smooth training of the machine learning model.

Then, we used a basic CNN network made of stacked convolutional, pooling, and fully connected layers. This CNN model was tasked with extracting relevant features from the input images and then learn to represent discriminative patterns for further classification. The CNN architecture had multiple convolutional layers preceded by max-pooling layers for detection of spatial features and reduction in dimensionality.

Furthermore, we investigated the possibility of using transfer learning by taking advantage of CNN models, like VGG and ResNet, for training both imbalanced and non-imbalanced data. Using transfer learning, our predictive model can benefit from the already acquired knowledge gained during the training phase using big datasets (e.g., ImageNet) which would speed up the learning process and in the end might improve the performance of our predictive model.

The study, involving tests based on the given approaches, revealed that the imbalanced datasets had significant performance gaps compared to the balanced datasets.

In case of imbalanced dataset, with the simple CNN model, we only moderately succeeded in classifying skin cancer lesions. In a like manner, transfer learning on the imbalanced dataset had some shortcomings such as the knock-off effected by an unbalanced class distribution, subsequently resulted in inferior performance.

Alternatively, the same pattern could be noted on the balanced dataset for the simple CNN model and the transfer learning-based approach, which all showed significant improvement in prediction accuracy. And by tackling the one-sided class distribution, the models became able to learn better representative and differentiable features, which consequently enhanced classification performance and the robustness of the model.

4.1 Exploratory Data Analysis:

A variety of significant steps were taken during the exploratory data analysis (EDA) which was performed on the skin cancer data set (HAM10000), in order to reveal the data and their characteristics.
For the first, in column Age is noticed values resembling 'NULL'. Because age column is significant for the kind of analysis and modelling to be done, the nulls where the field is missing in the rows were dropped to secure data consistency.

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

Fig 4.1

In addition, to this, entries that were duplicated were given place on the dataset. They noticed a common issue with images in the stack; many of them had different features but the same names. The duplicates were discovered and eliminated to ensure that the dataset didn't include the same entries over and over again, hence redundancy.
By making use of different presentation techniques the dataset was analyzed. Another important tool in data visualization was the graphs, bar graphs to be precise, box plots, and other data representations to understand the relationship and distribution of the data.

The following figures were generated as part of the EDA:
Localization Distribution by Sex: This drawing shows the distribution of skin cancer lesions as a function of the location (that is, the parts of the body where the disease has planted) and the genders of the studied patients. It allows to identify the higher incidence of some types of skin cancer during particular part of body in males and females.

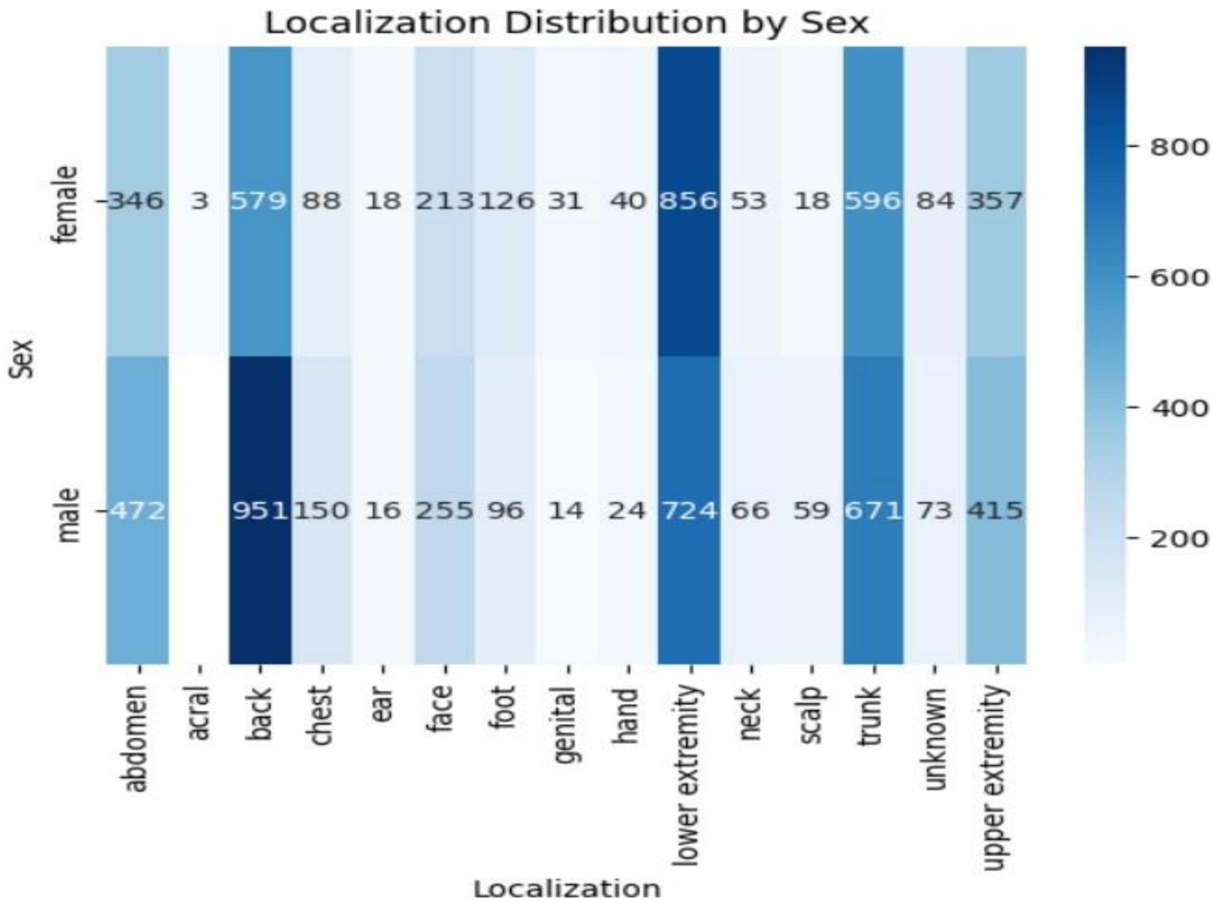


Fig 4.2

Localization of Skin Cancer by Sex: *The* graph is no much different form the last figure but is for the time frame of skin cancer lesions distribution by sex, and those specific locales are available for more detailed analysis of the trend.

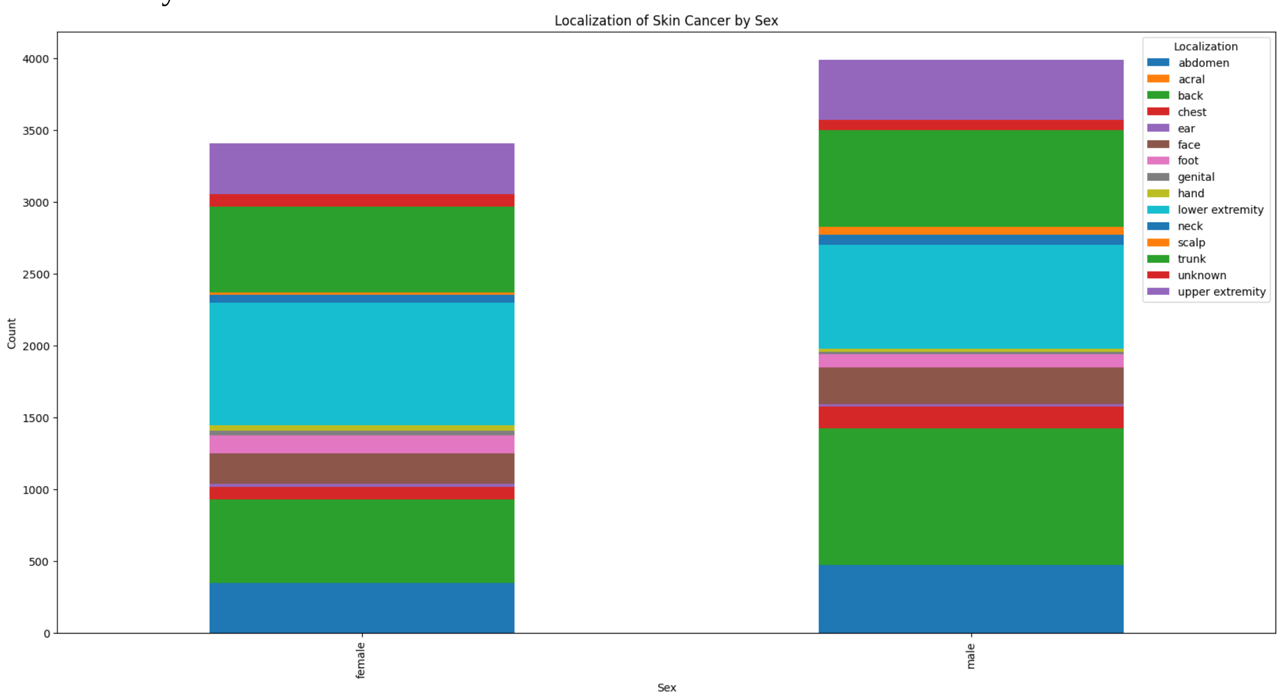


Fig 4.3

Percentage of Male and Female Cancer Patients: This chart, shows the percentage of women and men in data, allowing a sneak peek of gender distribution.

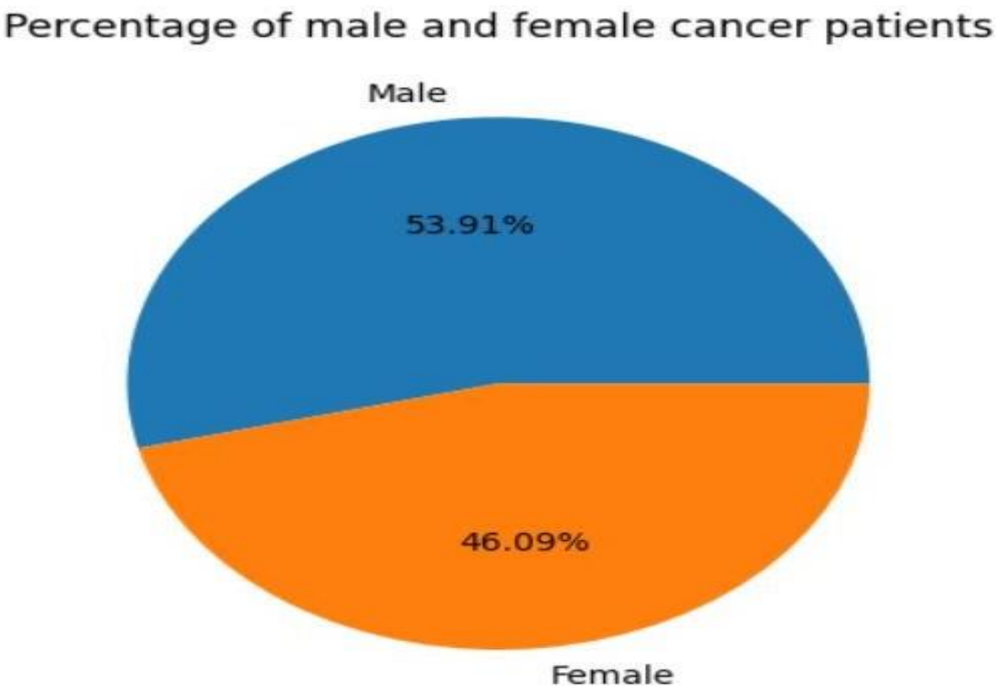


Fig 4.4

Frequency of Lesion Types: This category of visual presentation compares the number of different types of lesions which are in the data set.

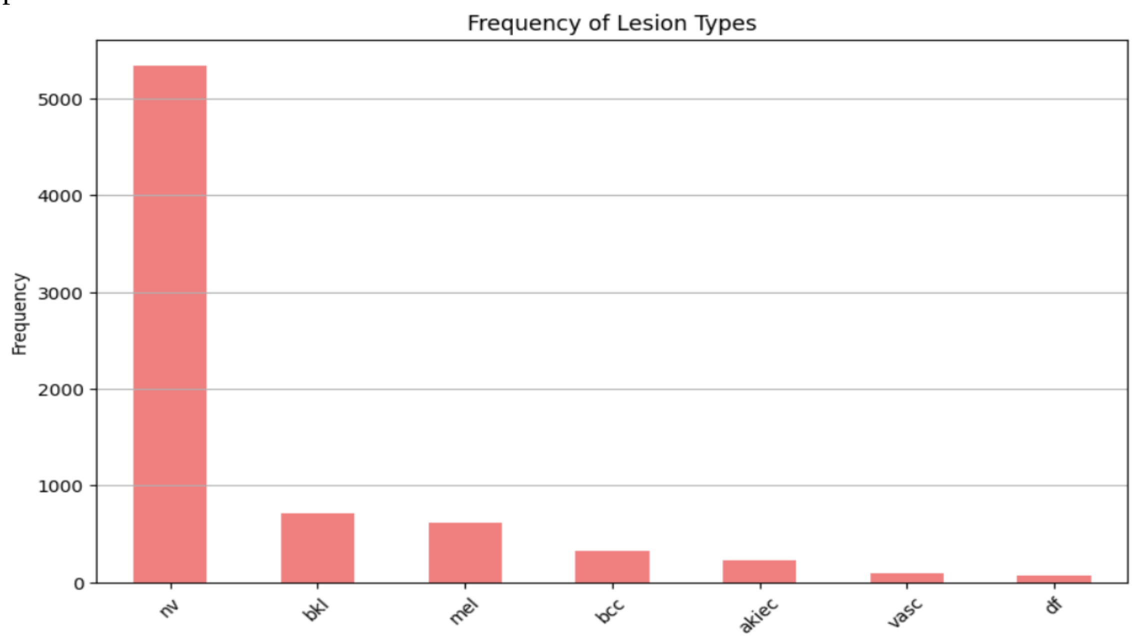


Fig 4.5

It assists in magnitude of manifestation of the each kind of the lesions and their domination in the dataset.

Distribution of Age by Lesion Type: A pie chart is given below to show in which age group most patients fall along with their skin lesion types.

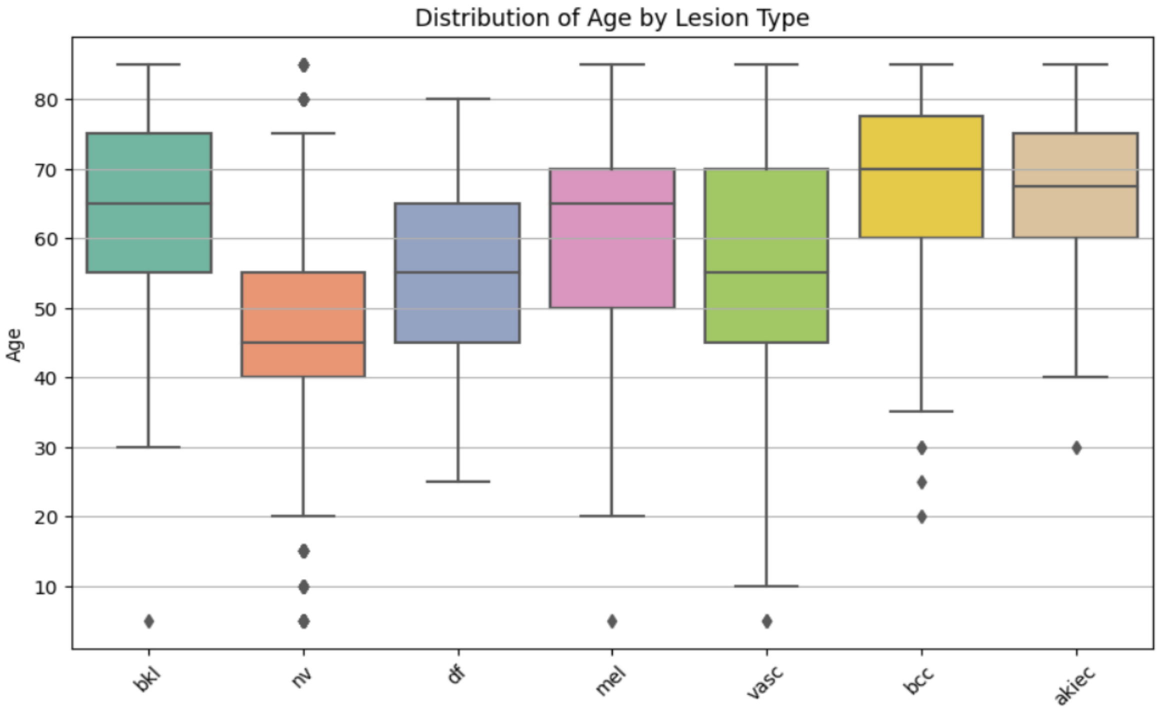


Fig 4.6

Ageing tendencies of the lesion type would be studied quantitatively in this model, providing the age-based classification of skin cancer patients.

Furthermore, the dataset imbalance in classification is another challenge. Therefore, it was necessary to balance the classes. This was aimed at protecting the model from class-biases and making it succeed with regards to all classes. Furthermore, set up of another column "image" enabled to keep the image matrix of all images with the predefined size. With this preprocessing stage, the data was ready for entering the model and it was ensured that the final analysis performed with the model was consistent data and by the rules.

Conducting with depth EDA and preprocessing tasks, the essential step is done giving useful guidance on the skin cancer dataset towards next steps such as modeling and analysis.

4.2 Training Process and Model Performance

We imported the required libraries from TensorFlow, including layers for constructing our neural network architecture, optimizers for optimizing the model parameters during training, loss functions for computing the difference between predicted and actual labels, and utility functions for data preprocessing.

Before training the model, we compiled it using the compile function provided by TensorFlow. This step involved specifying the optimizer, loss function, and evaluation metrics to be used during training. We chose the Adam optimizer, a popular choice for deep learning tasks, and the categorical cross-entropy loss function, suitable for multi-class classification problems like skin lesion

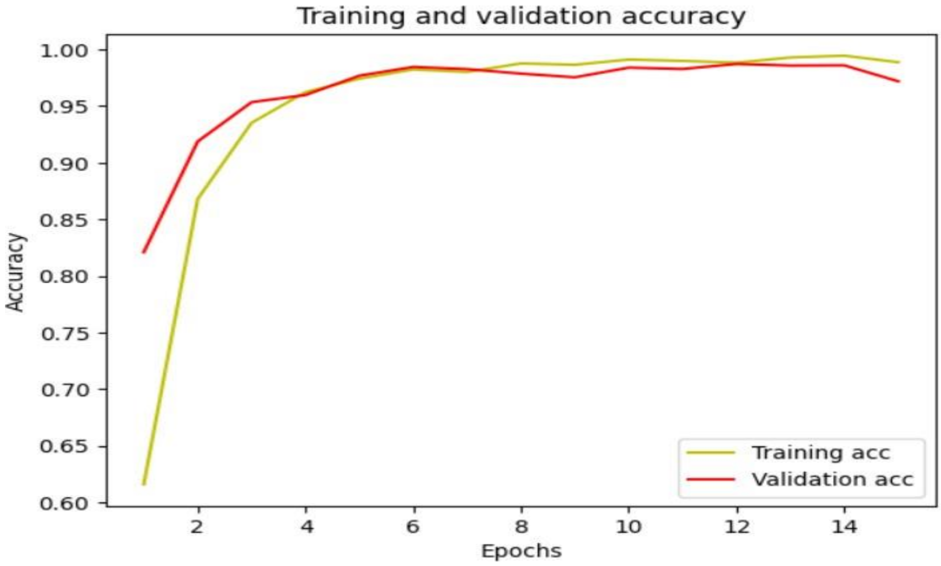


Fig4.7

With the model compiled, we proceeded to train it on our training data. We used the fit function, which takes as input the training data (x_train and y_train), the number of epochs (iterations over the entire dataset), batch size (number of samples processed together), and validation data for evaluating the model's performance on unseen data. During training, the model adjusts its parameters (weights and biases) based on the optimization algorithm (Adam) and the computed loss values, with the goal of minimizing the loss and improving predictive accuracy.

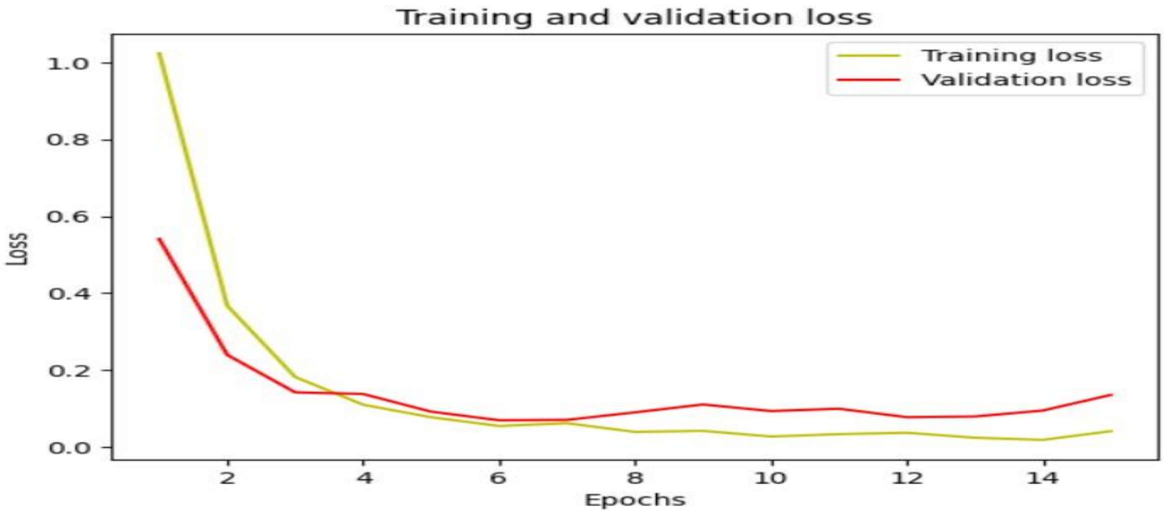


Fig4.8

Throughout the training process, TensorFlow provides updates on the model's performance via the history object. This object contains information such as the loss and accuracy metrics computed on both the training and validation datasets at each epoch. By monitoring these metrics, we can assess the model's learning progress and identify potential issues such as overfitting or underfitting.

4.3 Comparison of Different Models

The purpose of the comparison we are making of multiple models for skin cancer lesions prediction in this study was to determine how various pre-trained Convolutional Neural Network (CNN) architectures: VGG16, MobileNet, DenseNet121, and ResNet, performed. The various architectures have particular performance attributes in terms of the model's accuracy, the training time and the complexity of the structure of the model.

In terms of architectures adopted, the best result was the custom CNN model that yielded 98% of accuracy on the validation dataset. This accuracy proves the model's capability of rightly putting skin lesion images into their corresponding categories, and, therefore, it may be said that it is quite useful in helping with the diagnosis of skin cancer.

Apart from our in house designed CNN model, we investigated the option of transfer learning technique with pre-trained CNN systems as well.

VGG16, that has deep layers and it is very successful in image recognition tasks, gave much the same accuracy. Thus, VGG16 used a more complex structure and number of parameters that was time-consuming during the training.

Layer (type)	Output Shape	Param #
input_layer_2 (InputLayer)	(None, 65, 65, 3)	0
vgg16 (Functional)	(None, 2, 2, 512)	14,714,688
flatten_2 (Flatten)	(None, 2048)	0
dense_4 (Dense)	(None, 128)	262,272
dropout_2 (Dropout)	(None, 128)	0
dense_5 (Dense)	(None, 7)	903

Total params: 14,977,863 (57.14 MB)
Trainable params: 263,175 (1.00 MB)
Non-trainable params: 14,714,688 (56.13 MB)

Fig4.9

MobileNet, a lightweight CNN architecture that is developed particularly for the vision on mobile and embedded systems, attained highly satisfactory performance with signification less training time than VGG 16 which indicates its robust and low computational complexity.

Layer (type)	Output Shape	Param #
input_layer_4 (InputLayer)	(None, 65, 65, 3)	0
mobilenet_1.00_224 (Functional)	(None, 2, 2, 1024)	3,228,864
flatten_3 (Flatten)	(None, 4096)	0
dense_6 (Dense)	(None, 128)	524,416
dropout_3 (Dropout)	(None, 128)	0
dense_7 (Dense)	(None, 7)	903

Total params: 3,754,183 (14.32 MB)
Trainable params: 1,575,943 (6.01 MB)
Non-trainable params: 2,178,240 (8.31 MB)

Fig4.10

More simply than its predecessor, MobileNet produced quite accurate results, even when you take into account its complexity for the resource-constrained frameworks.
DenseNet121, known for the tight connectivity of their outputs that lead to the feature reuse and efficient gradient propagation, prove to have the best performance in the classification task of skin malformations. Deep learning DenseNet121 architecture achieved high prediction accuracy along with efficient information transmission between layers of the neural network.

Layer (type)	Output Shape	Param #
input_layer_6 (InputLayer)	(None, 65, 65, 3)	0
densenet121 (Functional)	(None, 2, 2, 1024)	7,037,504
flatten_4 (Flatten)	(None, 4096)	0
dense_8 (Dense)	(None, 128)	524,416
dropout_4 (Dropout)	(None, 128)	0
dense_9 (Dense)	(None, 7)	903

Total params: 7,562,823 (28.85 MB)
Trainable params: 564,231 (2.15 MB)
Non-trainable params: 6,998,592 (26.70 MB)

Fig4.11

It introduced a novel approach than other methods which made it a strong opponent in skin lesions prediction.
ResNet, on account of its depth and residual links is the one that has performed with the highest accuracy and low losses. ResNet was shown better to speed-up converge and reduce training time compared to VGG16, indicating to its higher efficiency in training deep neural networks.

Layer (type)	Output Shape	Param #
input_layer_6 (InputLayer)	(None, 65, 65, 3)	0
densenet121 (Functional)	(None, 2, 2, 1024)	7,037,504
flatten_5 (Flatten)	(None, 4096)	0
dense_10 (Dense)	(None, 128)	524,416
dropout_5 (Dropout)	(None, 128)	0
dense_11 (Dense)	(None, 7)	903

Fig 4.12

Generally, the reference between the models shows the power of the transfer learning and the necessity in the selection of suitable CNN architecture to forecasting of skin cancer lesions. While every architecture explores a unique route to excelling in accuracy, less computational resistance, and less complex model selection, our results have still contributed to exploring the right digital solution that will best serve the skin cancer patients' detection purposes.

4.4 Impact of Sampling Techniques on Performance

There is a significant bias in the distribution of labels within the skin cancer lesions dataset which raises a serious dilemma during model training and evaluation. Since the original dataset shows different populations across lesion types, from 142 for class 6 to 6705 for class 5, the model could

potentially be biased towards majority class and, thus, be less accurate when diagnosing the minority classes.
In order to rectify this imbalance and to reduce the risk of biases built in the model, sampling was used to form a more even dataset. On the page, we implemented a resampling approach which was used to achieve the class imbalance goal by over-sampling minority classes and under-sampling majority class. Thus, the purpose of such statistical measures is to guarantee the higher representation of each class in the training data which in turn, reduces the risk of bias and the model's ability to generalize to all classes.
Besides that, data augmentation techniques like rotation, flipping, and scaling were used to boost the data amount, but these methods proved to be rather inefficient when it came to leveling the data class imbalance and improving the models performance even further. So, sampling techniques' implementation started to be mandatory for data augmentation and increasing the data distribution and representation traits in each class.
As we were applying resampling during the training process, there was a more balanced classification of 6500 samples for each class. This balanced data set enabled the model to work harder and thus avoided tendencies to ignore some classes and focus on some others.
Sampling technique was instrumental as shown through the ensuing evaluation marks. The model conducted with a balanced dataset was seen to demonstrate better accuracy and generalization among all classes, as against training with the original imbalanced dataset Our model's capability to classify skin cancer accurately across different classes was heightened to by applying sampling techniques that targeted class imbalance. This further boosted its clinical utility.

4.5 Analysis of Evaluation Metrics

In our analysis of the skin cancer lesion prediction models, we used some evaluation metrics which helped us to see how well they can predict the category of skin lesions. The main metrics we employ in the analysis are accuracy, precision, recall, F1-score, and confusion matrix.
Accuracy:
Accuracy may perfectly define the correctness of model's predictions, which is a ratio of correctly labeled samples to the total number of samples. It presents a holistic view of the model performance by putting itself as an umbrella over all classes.
Precision:
The precision means how well the model is able to distinguish among the true positive predictions among all positive predictions. This aligns with the model's quality, specifically the accurate recognition, and the problem would be more severe in scenarios where false positives may have serious consequences.
Recall:
Recall, or sensitivity, is the count of the real positive prediction numbers out of all actual positive data. This property implies that the model can catch all positives (not overlook any positive instance) and is important when it is not favorable to miss any particular positive case.
F1-Score:
The F1-score is a harmonic mean of precision and recall and is measuring the result of the model in a balanced manner. It's about both false positive and false negative rates and when used well, it helps to measure models generalization performance when data exhibits a lot of imbalance.

Confusion Matrix:
The contingency table gives the original version of the model's predictions versus the actual class

labels as its table appearance. It disaggregates the classification performance into four sections based on the true positive, true negative, false negative and false positive predictions that indicates the model accuracy for various classes.

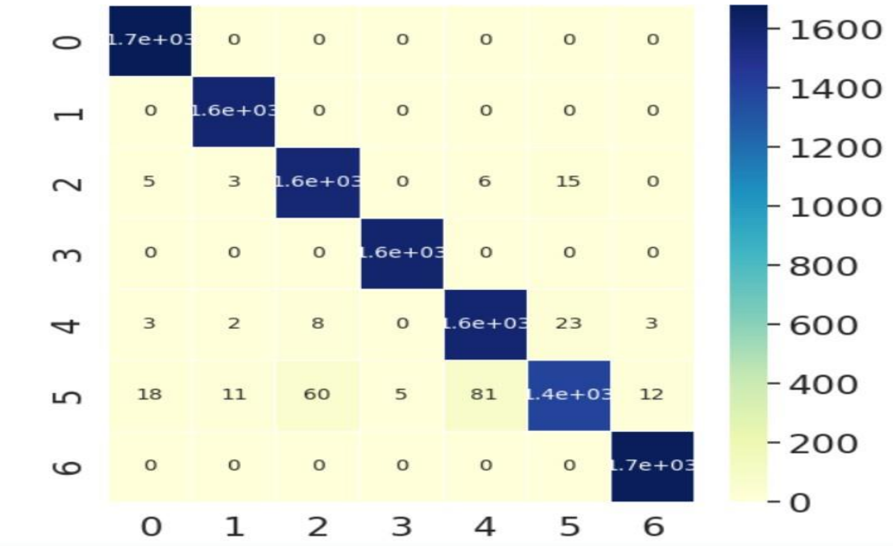


Fig 4.13

With regard to generating the evaluation reports having full details, we used the function of classification report from the sklearn.metrics module. The function does the calculation for precision, recall, F1 score, and support for each class and also the macro & weighted averages across all classes which serve as performance metrics of the model.

	precision	recall	f1-score	support
0	0.98	1.00	0.99	1681
1	0.98	0.98	0.98	1596
2	0.96	0.97	0.96	1607
3	0.99	0.96	0.98	1608
4	0.94	0.99	0.97	1637
5	0.95	0.90	0.92	1573
6	0.99	1.00	0.99	1673
accuracy			0.97	11375
macro avg	0.97	0.97	0.97	11375
weighted avg	0.97	0.97	0.97	11375

Fig 4.14

Interpreting the output matrix we provided confusion matrices using confusion_matrix() function to present distributions of correct and incorrect predictions across classes. These mtrices helped to identify the false assignment of positive or negative readings for classes and the areas where the model's predictions will improve.

Model	Accuracy	Precision	Recall
Normal CNN	98	98	98
VGG16	88	86	75
MobileNet	16	07	09
Densenet121	95	94	81
Resner50	94	90	80

Table 4.1

CHAPTER 5: MODEL DEPLOYMENT

5.1 Deployment Platforms and Considerations

During the skin cancer lesions prediction model deployment we faced the choice between different platforms and took into account the efficiency and availability of deployment. From the options of Streamlit, Flask, and Docker, where each of them has distinct features and advantages for model deployment, I considered them.

Streamlit emerged as our preferred deployment platform for several reasons:

User-Friendly Interface:
Streamlit is equipped with a friendly and easy-to-use interface for developing and deploying data science applications. Its straightforward and explicit syntax permits quick software development of interactive web apps that do not require long experience in front-end development.

Fast Iteration and Prototyping:
Streamlit provides developers with a chance to quickly test their applications with its real-time feedback and auto hot reload features. This helps in quickly switching between different model configurations and parameters, which speeds up the development process.

Integration with Machine Learning Libraries:
Streamlit easily combines commonly used machine learning libraries such as TensorFlow and scikit-learn, and now developers are able to connect their application with machine learning models. This kind of interoperability simplifies the procedure of deploying trained models and enables the development of end-to-end machine learning pipelines.

Rich Visualization Capabilities:
Streamlit provides a wide array of visualization options, including interactive charts, tables and

widgets which you can use to present and explore data driven insights. These visualization tools improve the interpretability and the user's experience of the deployed application allowing better understanding and decision-making.

Scalability and Deployment Options:
Unlike most tools that were designed solely for prototyping and development, Streamlit provides cloud-based deployment that can be easily scaled up to serve full production applications. Developers have the opportunity to deploy the Streamlit app on all kinds of platforms, including cloud services such as Heroku and AWS. This will ensure the end-users of the application on-the-go and even larger scale access.
In such regard, we concluded that Streamlit is our first choice in deploying machine learning systems, though Flask and Docker still offer feasible alternatives for such incorporation. Wrapper function Flask offers web pages building, especially for developers, a light framework that surpasses most modern ones in terms of flexibility and customization. Concerning Docker, however, the containerization feature will be put at disposal, giving developers the liberty to stamp their applications as well as dependencies at the same time into deliverable containers for use in any environment.

5.2 Integration with Web Applications

Integrating machine learning models with web applications is every effort if predictive features are to be made readily available to clients. Given that different deployments platforms are available, Streamlit became one of our preferable solutions. The probing benefits and the easy-to-use function led us to choose this one.
Streamlit grants an interface which is easy to operate that enables programmers to implement web applications with front-end interface in a quick way without having to have experience about front-end development. Its human language and speedy feedback make consequent attempts and prototyping easier than it has ever been as it enables developers to try different models' parameters in different ways and select the best model fast.
One of Streamlit's enviable assets is its tight outbuilding with TensorFlow and scikit-learn, which are familiar libraries. Humanizing Input: By incorporating trained models into the MLOps framework, the deployment process is streamlined, and complex machine learning pipelines will be produced. Developers are able to include machine learning models in their apps making use of Streamlit as means that can certainly be considered as an enhancement for their application which is meant for usefulness.
Not only that, but the platform also has rich visualization capabilities, where charts, tables, and widgets that can be manipulated give data and application users the same feel of looking through a tool or dashboard. The interactive tools build data-driven knowledge in the users, creating a deeper appreciation for the subject it convey and hence, better decision-making.
In fact, Streamlit is not the only solution as Flask and one more platform called Docker are the several good choices as well. With Flask being a weight-free and developer-friendly framework, it offers more advantageous options to increase the possibilities for developing customized applications, as Docker is the tool for containerization providing tools for any host-environment.

5.3 User Interface Design for Skin Lesion Detection

Our UI designers for the application of skin lesion detection has process based on simplicity and

interactivity and ready accessibility all by means of the step by step instructions.
Let's analyze the code and discuss the design elements:
Tab Navigation: The app incorporates the st.tabs feature to maintain the organization of information among the multiple tabs. Tabs utilized distinguish information type: the first tab focuses on the facts about skin cancer, the second provides data analysis, the third is devoted to the model, and finally some charts.

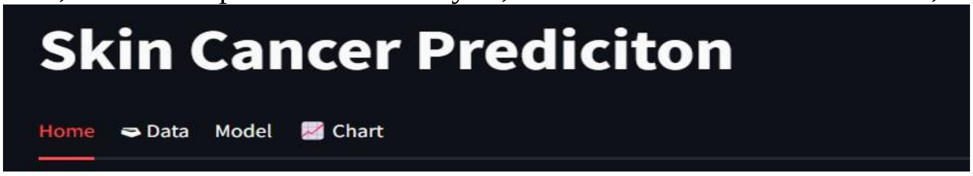


Fig5.1

It is this tab-based navigation which adds to the organizational and logical discipline of the application which makes it very easy for the users to change the tabs and switch between selective areas.
Tab Content: Each tab contains text in markdown, or data frames in interactive elements. To give another illustration, the “Home" page is a starting point that you can use to find skin cancer, its significance, and the dataset applied.

"Data" tab exhibits the dataset in a structured form by using the st.dataframe function operator within a "+" sign expansion, thereby provisioning users to the possibility of sifting through the raw data. The “Model" tab initinlizes the trained ML model and delivers a GUI for uploading images for prediction.

File Uploader: "Model" tab where a file uploader component named `st.file_uploader` is deployed for the users to upload the dermatoscopic images of skin lesions.

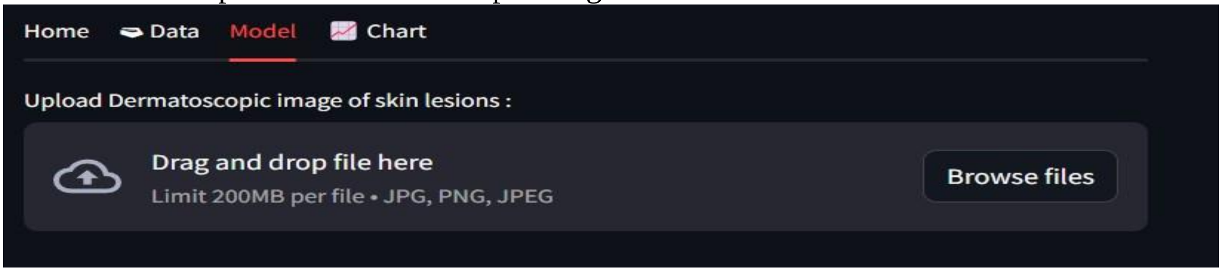


Fig5.2

It can be done through the interface of the model, which accepts input data for forecasts.

Prediction Display: Following the upload, the application uses the model to Inference the image and its output is displayed together with the relevant information of the predicted cancer type, its symptoms and the overall health situation.

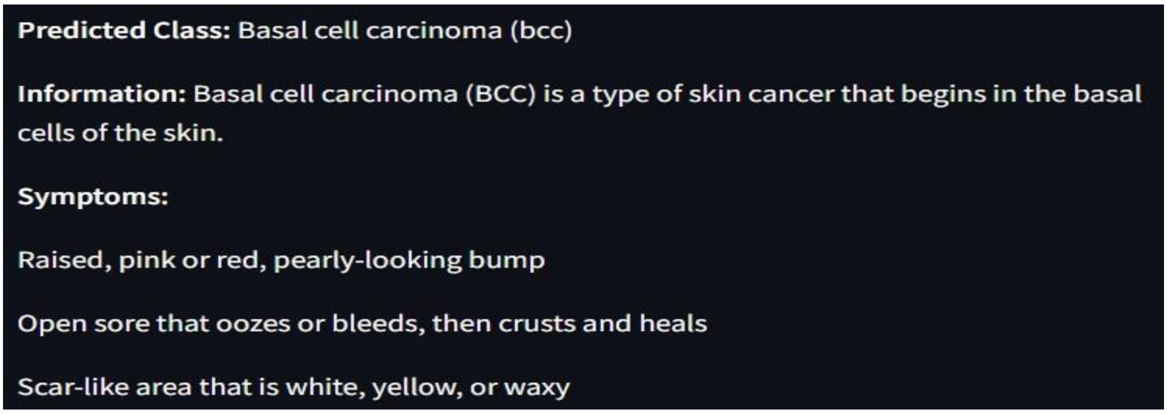


Fig5.3

This feedback mechanism further improves user involvement and absorption of the model's accuracy and correctness.

Chart Visualization: "Chart" tab provides the bar chart of the model predictive result. A graph shows a probability percentage for each label. Thus, users can understand a class label distribution quite visibly.

Responsive Layout: The application design is prepared for adaptability, thus, content is viewed properly on different device but (alike) screens size. Her layout features including st.set_page_config and use_column_width allow to make the user see appealing and easy to use interface.

CHAPTER 6: DISCUSSION AND CONCLUSION

6.1 Summary of Findings

Our skin cancer detection study process brought to light an array of issues and discoveries that have shaped our journey. Initially, HAM10000 dataset clarified the class imbalance as the biggest problem we face. We, however, had to turn into the world of sampling techniques which we did with due on the journey of the model architectures, from very basic CNNs to the sophisticated depths of transfer learning with pretrained models such as VGG16 and DenseNet121, each new step seemed to be leading to something even better. Evaluation came to be the main guide that led us through this clutter of metrics - accuracy, precision, recall, and the enigmatic F1-score - offering us invaluable information about our models' performance. Ultimately, the best was reached when our model was deployed in a user friendly interface using Streamlit. By means of creativity, innovation, and precise attention to detail, our expedition has not only demonstrated the case of improving the field of skin cancer detection but also is an example of the transformative influence of multidisciplinary teamwork in health care innovation.

6.2 Contributions of the Study:

The variety of our results, reflecting our commitment to improvement and advancement of the classification of skin cancer methodologies, are of a multifaceted nature. With the core of investigation we are adamant there is a real need for tests which are rapid and accurate to help tackle the problem of skin cancer, a deadly condition if not diagnosed early on. Utilizing advantageously of deep learning and computer vision, we launched a journey to find a strong network that can discern skin lesions with unmatched precision. Another crucial element of our contribution is the implementation of a new algorithm to compensate for the imbalance of datasets available from the HAM10000 dataset. Hence, we look at data imbalance due to biased distribution and determine data augmentation technique as a viable strategy that will promote equality and enhance the fairness of skin lesion categories. Therefore, this initial task set the stage for future model training and assessment, whereby the models were accurately calibrated to handle the complexities of different skin lesions observed in medical clinics.

Besides, the study becomes proof of success of collaboration and cross-discipline research as while in partnership with specialists from different areas, we worked through the complexities of model architecture selection, hyperparameter tuning, and performance evaluation. By using a comprehensive experimental design and a rigorous evaluating model, we tried to find the superior structure of a deep convolutional neural network (DCNN) for the classification of skin cancer. Our comparative experiments were of two types. Firstly, we used custom architectures and the secondly, we had established pretrained models such as VGG16 and VGG19. Our experiments provided us the knowledge about their strengths and weaknesses. Most importantly, the results that were obtained demonstrated that our custom DCNN model is superior to pretrained architectures which revealed that the model is robust and resilient in contrast to the diverse dermatoscopic data set.

Looking ahead, our study opens the door to a myriad of future research directions and opportunities for innovation. The successful validation of our framework on the HAM10000 dataset paves the way for its extension to other skin cancer datasets, offering the potential to enhance its generalizability and clinical applicability. Moreover, the exploration of additional metadata provided within the dataset holds promise for further improving the model's performance and diagnostic accuracy. As we continue to push the boundaries of skin cancer detection, our study serves as a beacon of hope for patients and clinicians alike, offering a glimpse into a future where advanced computational tools and artificial intelligence converge to revolutionize dermatological diagnosis and patient care.

6.3 Limitations and Future Directions

Although our project has accomplished a lot, there are still some things we should consider, and which will promote further exploration in the domain of this research. Indeed, the data augmentation approach helped us to overcome the dataset imbalance issue, however, it is also not without its limitations. The process of augmentation may give rise to synthetic artifacts or distortions that may in turn influence the performance of the model. Therefore, it is imperative to keep on experimenting with better augmentation techniques or data preprocessing methods to minimize these undesirable outcomes. Moreover, our use of HAM10000, as extensive as it is, might not encompass totally all the types of skin lesions that occur in clinical practice. Further studies could improve accuracy through the usage of additional datasets and real-life clinical data, which could enhance the generalizability and reliability of the models developed.

Additionally, the transparency and the interpretability of the deep learning models in medical imaging still remain a challenge. Although our models achieve high validation accuracy, there is no clearness about the decision making process and identification of salient features is not available. This limitation can be overcome by using interpretable deep learning frameworks or post-hoc interpretability techniques that would clarify the reasons behind the model predictions and would allow clinicians to understand and adopt the new technology.

Peeking ahead, a number of very bright opportunities are shimmering in the way of future research on skin cancer classification. Continued developments in deep learning architectures and techniques gives us a chance to improve models and make them multifunctional. Exploring various ensemble

models, for example, model aggregation or stacking which are more superior, may also result in synergy by harnessing the strengths of more models to obtain extraordinary accuracy. Furthermore, combination of multi-modal data sources, comprising clinical metadata, patient demographics, histopathological findings, etc., may function as a catalyst of improved diagnostic outcomes and targeted therapeutic approaches for the patients.
Also, our models should be adequately validated to use in the real-world clinical setting and given regulatory approval in order to guarantee patient safety and efficacy. Working together researchers, professionals, and regulatory communities must overcome for the space in medical device regulation and turning their findings to clinical practice.
Thus, although our study is a milestone in the research skin cancer classification, it is only a single step towards improving the general condition of patients and decreasing the cancer burden. That a step to acknowledge and to address the restrictions of our current approach will open the path to future innovations and investments that promise to revolutionize the skin-related diagnoses as well as therapy.

REFERENCES

[1] Diab, Amal G., Nehal Fayez, and Mervat Mohamed El-Seddek. "Accurate Skin Cancer Diagnosis Based on Convolutional Neural Networks." Indonesian Journal of Electrical Engineering and Computer Science 25, no. 3 (March 1, 2022).

[2] Dildar, Mehwish, Shumaila Akram, Muhammad Irfan, Hikmat Ullah Khan, Muhammad Ramzan, Abdur Rehman Mahmood, Soliman Ayed Alsaiari, Abdul Hakeem M Saeed, Mohammed Olaythah Alraddadi, and Mater Hussen Mahnashi. "Skin Cancer Detection: A Review Using Deep Learning Techniques." International Journal of Environmental Research and Public Health 18, no. 10 (May 20, 2021).

[3] Gururaj, H. L., N. Manju, A. Nagarjun, V. N. Manjunath Aradhya, and Francesco Flammini. "DeepSkin: A Deep Learning Approach for Skin Cancer Classification." IEEE Access 11 (2023): 50205–14.

[4] Alam, Talha Mahboob, Kamran Shaukat, Waseem Ahmad Khan, Ibrahim A. Hameed, Latifah Abd. Almuqren, Muhammad Ahsan Raza, Memoona Aslam, and Suhuai Luo. "An Efficient Deep Learning-Based Skin Cancer Classifier for an Imbalanced Dataset." Diagnostics 12, no. 9 (August 31, 2022): 2115.

[5] Beeler, Nadja, Esther Ziegler, Alexander A. Navarini, and Manu Kapur. "Factors Related to the Performance of Laypersons Diagnosing Pigmented Skin Cancer: An Explorative Study." Scientific Reports 13, no. 1 (December 21, 2023):

[6] Mirzargar, Mahsa, Ross T. Whitaker, and Robert M. Kirby. "Curve Boxplot: Generalization of Boxplot for Ensembles of Curves." IEEE Transactions on Visualization and Computer Graphics 20, no. 12 (December 31, 2014): 2654–63.

[7] Batista, Lucas G., Pedro H. Bugatti, and Priscila T.M. Saito. "Classification of Skin Lesion through Active Learning Strategies." Computer Methods and Programs in Biomedicine 226 (November 2022): 107122.

[8] Hao, Jiangang, and Tin Kam Ho. "Machine Learning Made Easy: A Review of Scikit-Learn Package in Python Programming Language." Journal of Educational and Behavioral Statistics 44, no. 3 (June 2019): 348–61.

[9] Nakatsu, Robbie T. "An Evaluation of Four Resampling Methods Used in Machine Learning Classification." IEEE Intelligent Systems 36, no. 3 (May 1, 2021): 51–57.

[10] Sae-Lim, Wannipa, Wiphada Wettayaprasit, and Pattara Aiyarak. "Convolutional Neural Networks Using MobileNet for Skin Lesion Classification." In 2019 16th International Joint Conference on Computer Science and Software Engineering (JCSSE), 242–47. Chonburi, Thailand: IEEE, 2019. P a g e 7 | 7

[11] Zheng, Linyi, and YuXing Dai. "M-VGG16: A Dermoscopy Image Segmentation Method Based on VGG16." In Third International Conference on Computer Vision and Data Mining (ICCVDM 2022), edited by Tao Zhang and Ting Yang, 21. Hulun Buir, China: SPIE, 2023.

[12] Al-masni, Mohammed A., Dong-Hyun Kim, and Tae-Seong Kim. "Multiple Skin Lesions Diagnostics via Integrated Deep Convolutional Networks for Segmentation and Classification." Computer Methods and Programs in Biomedicine 190 (July 2020).

[13] Panthakkan, Alavikunhu, S.M. Anzar, Sangeetha Jamal, and Wathiq Mansoor. "Concatenated XceptionResNet50 — A Novel Hybrid Approach for Accurate Skin Cancer Prediction." Computers in Biology and Medicine 150 (November 2022): 106170.

[14] Sadik, Rifat, Anup Majumder, Al Amin Biswas, Bulbul Ahammad, and Md. Mahfujur Rahman. "An InDepth Analysis of Convolutional Neural Network Architectures with Transfer Learning for Skin Disease Diagnosis." Healthcare Analytics 3 (November 2023): 100143.

[15] Duman, Erkan, and Zafer Tolan. "Comparing Popular CNN Models for an Imbalanced Dataset of Dermoscopic Images." Computer Science, September 16, 2021.

[16] Hengl, Tomislav. "Finding the Right Pixel Size." Computers & Geosciences 32, no. 9 (November 2006): 1283–98.

[17] Elangovan, Kabilan, Gilbert Lim, and Daniel Ting. "Medical Image Classification with On-Premise AutoML: Unveiling Insights through Comparative Analysis," July 25, 2023.

[18] Nwankpa, Chigozie, Winifred Ijomah, Anthony Gachagan, and Stephen Marshall. "Activation Functions: Comparison of Trends in Practice and Research for Deep Learning," 2018

[19] Yang, X.; Khushi, M.; Shaukat, K. Biomarker CA125 Feature Engineering and Class Imbalance Learning Improves Ovarian Cancer Prediction. In Proceedings of the 2020 IEEE Asia-Pacific Conference on Computer Science and Data Engineering (CSDE), Gold Coast, Australia, 16–18 December 2020; pp. 1–6.

[20] Szegedy, C.; Vanhoucke, V.; Ioffe, S.; Shlens, J.; Wojna, Z. Rethinking the inception architecture for computer vision. In Proceedings of the IEEE Conference on Computer Vision and

Pattern Recognition, Las Vegas, NV, USA, 27–30 June 2016; pp. 2818–2826.

[21] Szegedy, C.; Liu, W.; Jia, Y.; Sermanet, P.; Reed, S.; Anguelov, D.; Erhan, D.; Vanhoucke, V.; Rabinovich, A. Going deeper with convolutions. In Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition, Boston, MA, USA, 7–12 June 2015; pp. 1–9.

[22] Ali, I.S.; Mohamed, M.F.; Mahdy, Y.B. Data augmentation for skin lesion using self-attention based progressive generative adversarial network. arXiv 2019, arXiv:1910.11960.

[23] Krois, J.; Mahmood, A. Generalizability of deep learning models for dental image analysis. Sci. Rep. 2021, 11, 6102.

[24] Shrestha, A.; Mahmood, A. Review of deep learning algorithms and architectures. IEEE Access 2019, 7, 53040–53065.


thank you

Checklist for Dissertation-III Supervisor

Name:____________________________UID:_________Domain:_______
Registration No: 12017006   Name of student: Arindam Singh Thakur

Title of Dissertation:

Skin Cancer Detection

☐ Front pages are as per the format.
☐ The topic on the PAC form and title page are same.
☐ Front page numbers are in roman and for report, it is like 1, 2, 3…….
☐ TOC, List of Figures, etc. match the actual page numbers in the report.
++++

Signature of Supervisor with UID

Final_Report_Skin_Cancer 4th year (1).pdf

ORIGINALITY REPORT

11%	7%	6%	4%
SIMILARITY INDEX	INTERNET SOURCES	PUBLICATIONS	STUDENT PAPERS

PRIMARY SOURCES

1	dspace.lpu.in:8080 Internet Source	2%
2	Submitted to University of Salford Student Paper	1%
3	www.mdpi.com Internet Source	1%
4	"Proceedings of the 2nd International Conference on Big Data, IoT and Machine Learning", Springer Science and Business Media LLC, 2024 Publication	<1%
5	Submitted to Liverpool John Moores University Student Paper	<1%
6	fastercapital.com Internet Source	<1%
7	Submitted to University of Liverpool Student Paper	<1%
8	link.springer.com Internet Source	<1%