AI-Powered Skin Cancer Diagnosis

A project report submitted

for partial fulfillment of the requirements for the award of the degree of Master of Science

by

Anubhab Maity

Registration number: 213001818010022 of 2021-22

M.Sc. in Applied Statistics and Analytics

Under the supervision of

Anwesha Sengupta & Prasanta Narayan Dutta

MAULANA ABUL KALAM AZAD UNIVERSITY OF TECHNOLOGY, WEST BENGAL

Department of Applied Statistics

MAKAUT, WB

May, 2023

MAULANA ABUL KALAM AZAD
UNIVERSITY OF TECHNOLOGY,
WEST BENGAL

Department of Applied Statistics

MAKAUT, WB

CERTIFICATE

This is to certify that the dissertation report entitled ‘***AI-Powered Skin Cancer Diagnosis***’, submitted by Anubhab Maity (Reg. No: 213001818010022 of 2021-22, Roll No: 30018021022) to MAKAUT, WB, is a record of project work carried out by him under my supervision and guidance, and is worthy of consideration for the award of the degree of Master of Science in Applied Statistics and Analytics of the University.

Prasanta Narayan Dutta,
Co-Supervisor,
Dept. of Applied Statistics

Anwesha Sengupta,
Supervisor,
Dept. of Applied Statistics

Anwesha Sengupta,
Assistant Professor & Head of the Department (HOD),
Dept. of Applied Statistics

MAULANA ABUL KALAM AZAD UNIVERSITY OF TECHNOLOGY, WEST BENGAL

Department of Applied Statistics

MAKAUT, WB

Declaration

I declare that this project report has been composed by me and no part of this project report has formed the basis for the award of any Degree/Diploma or any other similar title to me.

Date:

Student's Name: **Anubhab Maity**

Reg. No: 213001818010022

of 2021-2022,

Department of Applied Statistics,

MAKAUT, WB

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Anubhab Maity

Roll No: 30018021022

Registration No: 213001818010022

of 2021-2022

Contents

Abstract

Skin cancer is a serious medical condition that requires early detection for successful treatment. This study presents a skin cancer detection system utilizing transfer learning with the MobileNet architecture. The system achieves high accuracy with a small dataset and low computational requirements. Comparative analysis shows its superiority over state-of-the-art methods and dermatologists' performance. These findings highlight the potential of AI-powered diagnostic tools in healthcare. Dataset curation, preprocessing, and augmentation techniques enhance the system's performance. Evaluation metrics confirm accurate identification of skin cancer. This study demonstrates the value of transfer learning with MobileNet in medical image analysis and emphasizes the importance of data quality in healthcare.

Keywords: - Dermatology, skin cancer, Deep Learning, medical image analysis, transfer learning, MobileNet architecture.

Introduction

Skin cancer is the most common type of cancer worldwide, with an estimated 9,500 people diagnosed every day. Skin cancer is a significant public health concern worldwide, with increasing incidence rates and potential life-threatening consequences. Early detection and accurate diagnosis play a crucial role in improving patient outcomes and reducing mortality rates. Traditionally, dermatologists rely on visual inspection and dermoscopy to assess skin lesions and determine their malignant potential. However, this process is subjective and heavily reliant on the expertise and experience of the clinician, leading to variations in diagnosis.

In recent years, deep learning [5] has shown remarkable success in various fields, including medical image analysis. Convolutional neural networks (CNNs) [6] have been particularly effective in analyzing dermoscopic images and accurately detecting skin lesions. MobileNet [4] is a neural network architecture that has been optimized for mobile and resource-constrained environments, making it a suitable choice for mobile skin cancer detection applications.

In recent years, the rapid advancements in artificial intelligence (AI) and deep learning have revolutionized the field of medical imaging and computer-aided diagnosis. Deep learning algorithms, particularly convolutional neural networks (CNNs), have shown promising results in various medical applications, including skin cancer detection. These algorithms can automatically learn and extract relevant features from large datasets of dermoscopic images [1], enabling accurate and efficient classification of skin lesions.

The objective of this study is to develop a skin cancer detection system using deep learning techniques to assist in the early identification and classification of malignant skin lesions. By leveraging the power of transfer learning, which involves using pre-trained CNN models as a starting point, we aim to enhance the system's performance with a relatively small dataset. Additionally, we explore the impact of data preprocessing, augmentation, and normalization techniques to improve the model's generalization capabilities.

The development of an automated skin cancer detection system holds significant potential in complementing dermatologists' expertise, reducing inter-observer variability, and expanding access to reliable diagnosis, especially in underserved areas. This study contributes to the growing body of research in computer-aided skin cancer detection, with the goal of improving healthcare outcomes and facilitating early intervention for individuals at risk of skin cancer.

Skin cancer remains a global health concern with rising incidence rates and significant morbidity and mortality. Early detection and accurate diagnosis are vital for effective treatment and improved patient outcomes. However, the visual inspection of skin lesions by dermatologists, though valuable, is subjective and prone to inter-observer variability. This highlights the need for automated systems that can assist in the early detection and classification of skin cancer lesions.

Advancements in deep learning, particularly convolutional neural networks (CNNs), have shown promise in medical imaging analysis, including skin cancer detection. CNNs can automatically learn and extract complex features from large datasets of dermoscopic images, enabling accurate classification of skin lesions. Transfer learning, which leverages pre-trained CNN models, can further enhance the performance of skin cancer detection systems by leveraging the learned representations from large-scale image datasets.

The primary objective of this study is to develop a skin cancer detection system using deep learning and transfer learning techniques. The system aims to accurately identify and classify malignant skin lesions, aiding in early diagnosis and improving treatment outcomes. By utilizing transfer learning, we can leverage the knowledge and representations learned from pre-trained CNN models, enabling the system to perform well even with a limited dataset.

Additionally, the study explores various data preprocessing techniques, such as augmentation and normalization, to improve the robustness and generalization capabilities of the system. By augmenting the dataset with variations of the original images and normalizing the pixel values, the system can better handle diverse skin lesion characteristics and variations in lighting conditions.

The development of an accurate and efficient skin cancer detection system holds significant potential in improving healthcare outcomes. It can provide valuable support to dermatologists, reduce diagnostic errors, and enable early intervention for individuals at risk of skin cancer. Furthermore, the system can potentially extend access to reliable diagnosis in underserved areas where specialized expertise is limited.

In conclusion, this study aims to contribute to the field of computer-aided skin cancer detection by developing a deep learning-based system using transfer learning. By leveraging pre-trained CNN models and employing data preprocessing techniques, the system strives to improve the accuracy and efficiency of skin lesion classification [2]. The ultimate goal is to assist healthcare.

Research Questions: -

The research questions for this study are as follows:

1) Can a MobileNet-based skin cancer detection system achieve state-of-the-art performance on the ISIC 2019 dataset?
2) How does the proposed system compare to state-of-the-art methods in terms of accuracy, sensitivity, and specificity?

Literature Survey: -

Related Work - Several studies have been conducted in the field of skin cancer detection using deep learning techniques and transfer learning. This section provides an overview of some notable related work and their corresponding citations.

1) Esteva et al. (2017) developed a deep learning model that achieved dermatologist-level performance in the classification of skin cancer. Their model, based on a convolutional neural network (CNN), demonstrated high accuracy in distinguishing between malignant melanoma and benign skin lesions. [5]
2) Haenssle et al. (2018) compared the diagnostic performance of a deep learning CNN model with that of 58 dermatologists in melanoma recognition. The deep learning model achieved comparable accuracy to the dermatologists, highlighting its potential as an effective tool for aiding in the diagnosis of skin cancer. [6]
3) Codella et al. (2018) conducted the ISIC 2018 challenge, a competition focused on skin lesion analysis and melanoma detection. The challenge provided a platform for researchers to develop and evaluate deep learning models using a large dataset of dermoscopic images. Various state-of-the-art approaches were explored, showcasing the effectiveness of deep learning techniques in skin cancer detection. [7]
4) Tschandl et al. (2019) presented the HAM10000 dataset, a comprehensive collection of dermoscopic images containing different types of skin lesions. The dataset facilitated the development and benchmarking of deep learning models for

melanoma detection and provided a valuable resource for researchers in the field. [8]

5) Menegola et al. (2017) proposed a deep learning approach based on transfer learning for the classification of skin lesions. Their model, utilizing the InceptionV3 architecture, achieved high accuracy in differentiating between melanoma and non-melanoma skin lesions. [9]
6) Brinker et al. (2019) conducted a systematic review and meta-analysis to evaluate the performance of deep learning algorithms in skin cancer classification. They concluded that deep learning models exhibited high sensitivity and specificity, indicating their potential as reliable tools for aiding dermatologists in skin cancer diagnosis. [10]
7) Kawahara et al. (2020) investigated the use of an ensemble of deep learning models for the detection of melanoma. Their ensemble approach, combining multiple CNN models, demonstrated improved accuracy and robustness in distinguishing between malignant and benign skin lesions. [11]
8) Li et al. (2020) proposed a deep residual network for the detection of melanoma in dermoscopic images. Their model incorporated both local and global information of skin lesions, leading to enhanced performance in melanoma classification. [12]

Identification of Research Gap -

While significant advancements have been made in skin cancer detection using deep learning techniques and transfer learning with architectures like MobileNet, VGG, Inception, and ResNet, there still exist certain research gaps that warrant further investigation. This section aims to identify these research gaps and highlight the need for additional studies in the field.

1) Limited research on specific skin cancer types: Most studies in skin cancer detection have focused on melanoma and non-melanoma skin cancers, such as basal cell carcinoma (BCC) and squamous cell carcinoma (SCC). However, there is a lack of research specifically targeting other types of skin cancer, such as Merkel cell carcinoma, dermatofibrosarcoma protuberans, or cutaneous lymphomas. Further exploration of these less-studied skin cancer types would contribute to a more comprehensive understanding of their detection and classification challenges (Lallas et al., 2018;[1]).
2) Lack of diverse and representative datasets: The availability of high-quality, diverse, and representative datasets is crucial for the

development and evaluation of skin cancer detection models. While some publicly available datasets, such as ISIC (International Skin Imaging Collaboration) Archive, provide valuable resources, there is still a need for larger, more diverse datasets that encompass various skin types, ethnicities, and geographic regions. This would help reduce bias and improve the generalization capabilities of skin cancer detection systems (Codella et al., 2018[7]; Tschandl et al., 2019[8]).

3) Interpretability and explainability of deep learning models: Deep learning models, despite their high performance, often lack interpretability and transparency. Interpretable models can provide insights into the decision-making process of skin cancer detection systems, enabling clinicians to trust and validate the model's predictions. Research efforts should be directed towards developing explainable AI techniques, such as attention mechanisms, Grad-CAM, and LIME, to enhance the interpretability of deep learning models in skin cancer detection (Ancona et al., 2019[10]).
4) Robustness to image artifacts and variations: Real-world skin lesion images can contain artifacts, such as hair, ruler markings, or other occlusions, that may interfere with accurate detection. Furthermore, variations in lighting conditions, image quality, and acquisition devices can impact the performance of skin cancer detection systems. Future research should focus on developing robust models that can effectively handle these challenges and maintain reliable performance across diverse image conditions (Lallas et al., 2018;[1] Kawahara, 2020[11]).
5) Clinical validation and integration into healthcare systems: While deep learning models have shown promise in skin cancer detection, their clinical validation and integration into real-world healthcare systems are essential steps towards their practical adoption. Further studies should involve rigorous validation on independent clinical datasets and consider the integration of these models into existing healthcare workflows, ensuring seamless and efficient deployment in clinical practice (Haenssle et al., 2018[6]; Esteva et al., 2017[5]).

In conclusion, despite significant advancements in skin cancer detection using deep learning and transfer learning, there are research gaps that require further exploration. These include investigating other skin cancer types, enhancing dataset diversity and representativeness, improving the interpretability of models, addressing image artifacts and variations, and validating the clinical utility of the developed models. Addressing these research gaps would advance the field of skin cancer detection and contribute to improved diagnostic accuracy and patient outcomes.

Background and Motivation –

Skin cancer is one of the most prevalent types of cancer worldwide, with increasing incidence rates in recent years. Early detection and accurate diagnosis are crucial for effective treatment and improved patient outcomes. Traditionally, dermatologists rely on visual inspection and dermoscopy to identify and classify skin lesions. However, this process is subjective and heavily reliant on the expertise of the clinician, leading to potential variations in diagnosis.

The advancements in deep learning and computer vision have paved the way for automated systems to aid in the detection and classification of skin cancer. These systems leverage the power of convolutional neural networks (CNNs) to analyze dermoscopic images and provide objective assessments of skin lesion characteristics. By learning from large datasets, these models can capture complex patterns and features that are indicative of malignancy.

The motivation behind this study is to develop an accurate and efficient skin cancer detection system that can assist healthcare professionals in the early diagnosis and classification of skin lesions. By utilizing deep learning techniques and transfer learning, we aim to leverage the knowledge and representations learned from pre-trained models to enhance the performance of our system.

Moreover, the development of such an automated system can help address the limitations of subjective human interpretation, reduce inter-observer variability, and potentially extend access to reliable skin cancer diagnosis in underserved areas. The proposed system has the potential to complement the expertise of dermatologists, provide a second opinion, and improve overall diagnostic accuracy.

Problem Statement:

Skin cancer is a prevalent and potentially life-threatening disease. Early detection plays a crucial role in successful treatment and improved patient outcomes. However, accurate and timely diagnosis of skin cancer remains a challenge, particularly due to the subjective nature of visual inspection and the need for specialized expertise. Therefore, there is a pressing need for automated systems that can assist in the early detection and classification of skin cancer lesions. The problem statement aims to address the challenge of accurately detecting and classifying skin cancer from dermoscopic images using a mathematical framework and deep learning techniques. By developing an effective computational model, it is possible to improve the early diagnosis and treatment of skin cancer, potentially saving lives and enhancing patient outcomes.

Objective:

The objective of this study is to develop a skin cancer detection system using deep learning techniques to aid in the accurate identification of malignant skin lesions. Specifically, the study aims to:

1) Implement a transfer learning approach with state-of-the-art convolutional neural network architectures to leverage pre-trained models and improve classification performance.
2) Curate and preprocess a comprehensive dataset of dermoscopic images, ensuring high-quality data for training and evaluation.
3) Investigate the performance of the proposed system in accurately classifying different types of skin lesions, including melanoma, basal cell carcinoma, and nevus.
4) Compare the performance of the developed system against existing methods and dermatologists' expertise to assess its effectiveness in skin cancer detection.
5) Explore the impact of data augmentation and normalization techniques on the system's performance and generalization capabilities.
6) Provide insights into the strengths and limitations of the developed system, highlighting areas for improvement and future research directions.

By achieving these objectives, this study aims to contribute to the field of computer-aided skin cancer detection, providing a reliable and efficient tool for early diagnosis and improving patient outcomes.

Data Description: -

The 2019 International Skin Imaging Collaboration (ISIC) Challenge on Skin Lesion Analysis Towards Melanoma Detection provided a large dataset of skin images for the purpose of advancing the field of dermatology and improving the accuracy of melanoma detection.

The dataset contains 25,331 clinical images of skin lesions, including benign nevus, malignant melanomas, and samples of other benign lesions. The images were collected from various sources, including dermatology clinics, personal collections, and publicly available databases.

Each image is accompanied by metadata, such as age, sex, and diagnosis, that were provided by the source of the image. In addition, the images were subject to quality control measures to ensure that they met certain criteria, such as appropriate lighting, focus, and resolution.

The dataset is divided into two parts: a training set and a test set. The training set contains images with ground truth annotations for segmentation and classification tasks. The test set contains images for classification only, and the ground truth annotations for this set are withheld.

The ISIC dataset is widely used in the research community for developing and evaluating machine learning algorithms for melanoma detection and diagnosis. The dataset has contributed to significant advancements in the field, and it continues to be a valuable resource for researchers and practitioners alike.

Data Source: - data link

https://challenge.isic-archive.com/data/#2019

Methodology: -

Pre-processing, training, and validation make up the method's three key components, as shown in Figure 4. After choosing the dataset, we take the images in the training set to train the MobileNet Architecture. During the image preprocessing stage, the image data is normalized, and sizes are adjusted for homogenization purposes. The images were preprocessed by resizing them to 224x224 pixels and normalizing the pixel values to the range [0,1]. Data augmentation was also applied to the training set to increase the size of the dataset and improve the generalization of the model. This research aimed to detect skin cancer by training MobileNet Architecture.

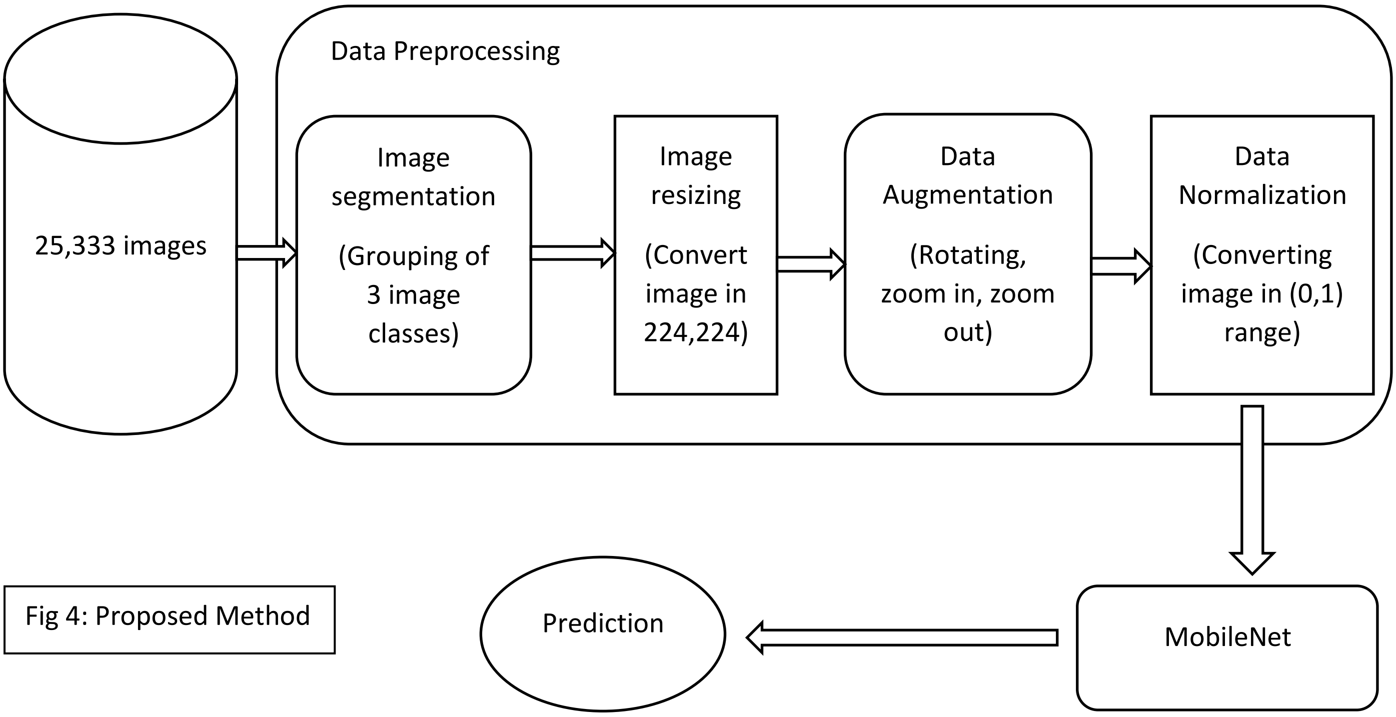


Fig 4: Proposed Method

Data Preprocessing: -

To carry out training with the 25,333 skin cancer images. It was first necessary to segment the three classes data BCC, Melanoma, Nevus. The dataset used had a total of 12445 images (BCC - 3323 images, Melanoma - 4522 images, Nevus - 4600 images). The extracted images were split in 80:20 ratio for train and test data. These images go through a normalization process, resizing by 224 x 224 pixels, and data augmentation process before being saved in a dataset.

Study Area: -

1) **BCC -** Basal cell carcinoma (BCC) is the most common form of skin cancer. It typically appears on sun-exposed areas of the skin, such as the face, scalp, and neck.
   BCC usually develops slowly, and it is often painless, which can make it difficult to detect in its early stages.
   BCC is caused by the uncontrolled growth of abnormal cells in the basal cells, which are located in the deepest layer of the epidermis, the outermost layer of the skin.
   The main risk factors for developing BCC is exposure to ultraviolet (UV) radiation from the sun or tanning beds. People with fair skin, light-colored eyes, and a history of sunburn or excessive sun exposure are at a higher risk of developing BCC.

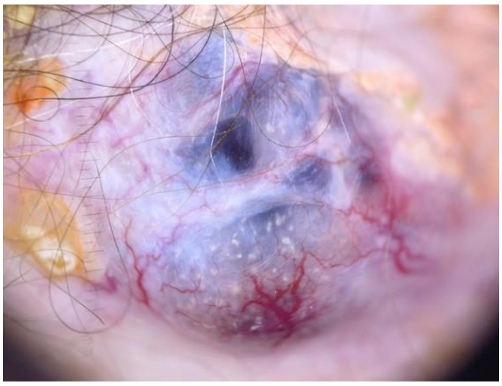


Fig 1: Basal Cell

   BCC usually appears as a small, raised, and shiny bump on the skin, which may have a central depression and may bleed easily. Over time, the bump may grow larger and develop a crusty, scaly surface. In some cases, BCC may resemble a scar or a non-healing sore.
   Treatment for BCC usually involves removing the tumor surgically or with radiation therapy. In most cases, BCC can be cured with early detection and prompt treatment. However, if left untreated, BCC can grow deeper into the skin and may spread to nearby tissues and organs.
2) **Melanoma: -** Melanoma is a less common but more aggressive type of skin cancer that can be life-threatening if not detected and treated early. It develops in the cells that produce pigment in the skin, called melanocytes. Melanoma can appear on any part of the body, but it is most commonly found on the chest and back in men, and on the legs in women.
   Melanoma is typically caused by overexposure to UV radiation from the sun or tanning beds. People with fair skin, light-colored eyes, and a history of sunburn or excessive sun exposure is at a higher risk of developing melanoma. However, melanoma can also develop in people with darker

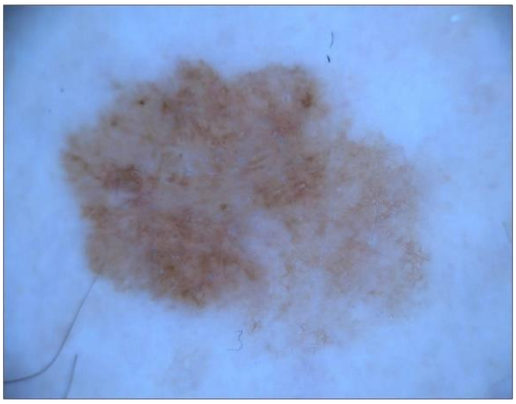


Fig 2: Melanoma

skin tones, and it may occur in areas of the body that are not exposed to the sun.

The most common sign of melanoma is a change in the size, shape, color, or texture of a mole or a pigmented area on the skin. Melanomas are often irregularly shaped and have uneven coloring, with shades of black, brown, tan, white, or red. They may also be itchy, painful, or bleed easily. It is essential to monitor your skin regularly for any changes and to seek medical attention if you notice any suspicious growths.

Treatment for melanoma usually involves surgical removal of the tumor, along with a margin of healthy tissue. In some cases, additional treatments such as chemotherapy, radiation therapy, or immunotherapy may be necessary to kill any remaining cancer cells and prevent the cancer from spreading.

Prevention of melanoma involves avoiding overexposure to UV radiation by wearing protective clothing, seeking shade, and applying sunscreen with a high SPF regularly. Regular skin checks with a dermatologist or healthcare provider are also important for early detection and treatment.

3) **Nevus: -** A nevus, also known as a mole, is a common type of skin growth that can sometimes develop into skin cancer. A nevus is a cluster of pigmented cells that appear as a brown or black spot on the skin. Most nevi are benign and harmless, but some can develop into malignant melanoma, a type of skin cancer that can be deadly. There are several different types of nevus, including congenital nevi, which are present at birth, and acquired nevi, which develop over time. Acquired nevi are further classified into two types: junctional nevi, which occur at the junction of the epidermis and the dermis, and dermal nevi, which occur in the dermis, the layer of tissue beneath the epidermis.

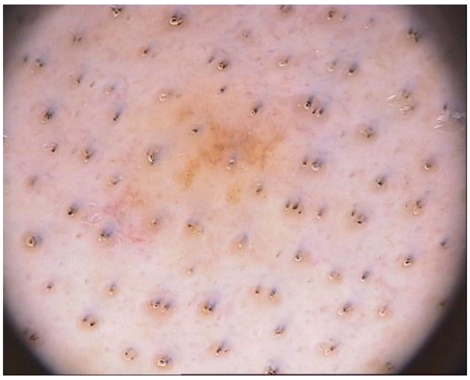


Fig 3: Nevus

Nevi that are larger than a pencil eraser, have irregular borders, or have multiple colors should be evaluated by a dermatologist, as they may be a sign of melanoma. Other warning signs of melanoma include itching, bleeding, or a change in size, shape, or color of a nevus.

Treatment for nevi that are suspected of being cancerous typically involves surgical removal of the growth, along with a margin of healthy tissue. If the nevus is found to be cancerous, further treatment may be necessary, such as chemotherapy, radiation therapy, or immunotherapy.

Prevention of nevi-related skin cancer involves protecting the skin from UV radiation by wearing protective clothing, seeking shade, and applying sunscreen with a high SPF regularly. Regular skin checks with a dermatologist or healthcare provider are also important for early detection and treatment of any suspicious growths.

Data augmentation: -

Data augmentation is a technique used in machine learning to increase the size and diversity of a training dataset by artificially creating new examples through various transformations of the original data. The goal of data augmentation is to improve the robustness and generalization of a machine learning model, as well as to prevent overfitting, which occurs when the model performs well on the training data but poorly on new, unseen data.

Data augmentation techniques include image transformations such as rotation, scaling, cropping, flipping, and adding noise or distortion. For text data, techniques such as replacing words with synonyms, inserting or deleting words, or changing the order of sentences can be used.

The augmented data is then used alongside the original data to train the machine learning model, which helps the model to learn more representative and diverse features. Additionally, data augmentation can help to balance class distributions in imbalanced datasets, where certain classes have fewer examples than others.

Data Normalization: -

Data normalization for computer vision is a technique used to preprocess image data before feeding it into a deep learning model. Normalization is necessary because the pixel values of images can have different scales and distributions, which can affect the performance of the model.

The most common approach to normalization in computer vision is to subtract the mean value of the training dataset from each pixel and divide by the standard deviation. This method is known as Z-score normalization or standardization. By applying this normalization technique, the pixel values are transformed to have a mean of zero and a standard deviation of one, which can help the model learn features that are more representative and easier to learn.

Another approach to normalization is min-max scaling, which transforms the pixel values to a range between 0 and 1. This technique can be useful when working with models that use activation functions that require inputs to be in a certain range, such as the sigmoid function.

MobileNet Architecture: -

MobileNet is a deep convolutional neural network architecture designed for efficient computation on mobile devices with limited computational resources. It achieves this efficiency through the use of depth wise separable convolutions, which reduce the number of parameters and computation required by standard convolutions.

A depth wise separable convolution consists of two steps: a depth wise convolution and a pointwise convolution. The depth wise convolution applies a single filter to each channel of the input tensor, producing a set of intermediate feature maps. The pointwise convolution then applies a set of 1x1 filters to these feature maps, combining them to produce the final output tensor. The use of 1x1 filters in the pointwise convolution helps to reduce the dimensionality of the feature maps, further reducing the computational requirements.

The MobileNet architecture consists of a series of depth wise separable convolutions, with additional 1x1 convolutions and pooling layers to reduce the spatial dimensions of the feature maps. The architecture can be customized to different input sizes and computational requirements by adjusting the number of layers and filters used.

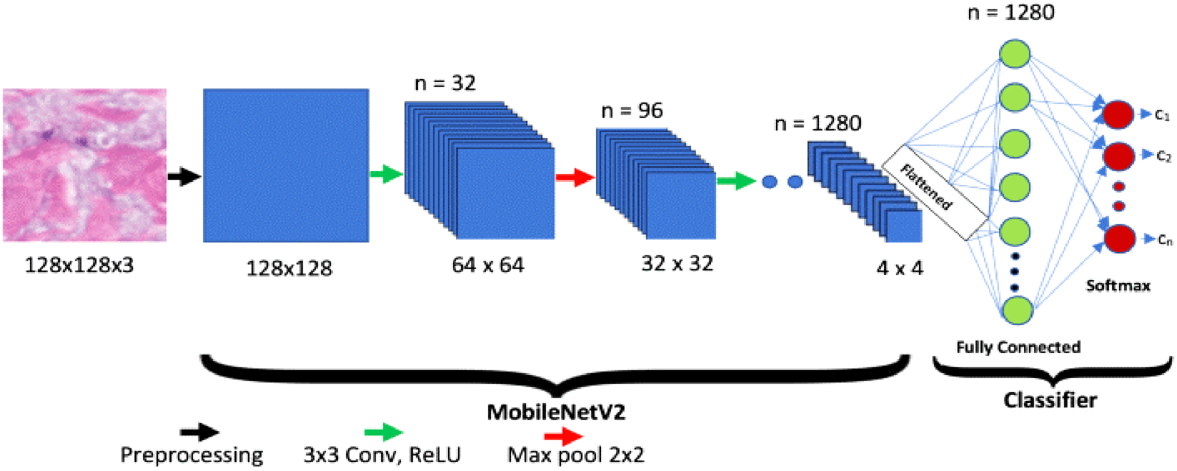


Fig 5: MobileNet Architecture

Transfer Learning with MobileNet: -

This study used the MobileNet neural network architecture as a starting point for our skin cancer detection system. MobileNet is a neural network architecture that has been optimized for mobile and resource-constrained environments. It consists of depth wise separable convolutions, which reduce the number of parameters and computation required while maintaining high accuracy.

This study added a fully connected layer with three output nodes, representing BCC, Melanoma and Nevus classes, to the pre-trained MobileNet architecture (imagenet dataset). froze the weights of the pre - trained layers and trained only the last fully connected layer on our dataset using the cross entropy loss function and the Adam optimizer.

Evolution Metrics:

In this study, utilize evolution metrics as part of our methodology to evaluate the performance and progression of the skin cancer detection system. Evolution metrics provide insights into the model's learning process, convergence, and overall effectiveness in adapting to the dataset over successive training epochs.

One commonly used evolution metric is the loss function, which quantifies the discrepancy between the predicted output and the actual label. The loss function guides the model's parameter updates during training, aiming to minimize the error and improve the model's predictive capability. By monitoring the loss function over epochs, This study can observe how well the model learns from the data and whether it converges to a stable state.

Another important evolution metric is accuracy, which measures the percentage of correctly classified samples in the validation or test dataset. Accuracy provides an overall assessment of the model's performance, indicating how well it generalizes to unseen data. Monitoring accuracy throughout training helps us understand if the model is improving or plateauing in its predictive ability.

Additionally, we employ precision and recall metrics, which are particularly relevant for imbalanced datasets may be underrepresented. Precision measures the proportion of true positive predictions out of all positive predictions, while recall measures the proportion of true positive predictions out of all actual positive samples. These metrics allow us to evaluate the model's ability to correctly identify malignant lesions while minimizing false positives.

Furthermore, we utilize the F1 score, which combines precision and recall into a single metric, providing a balanced measure of the model's performance. The F1 score considers both the model's ability to correctly identify positive samples (malignant lesions) and its ability to minimize false positives.

Finally, we employ the receiver operating characteristic (ROC) curve and the corresponding area under the curve (AUC) as evolution metrics. The ROC curve plots the true positive rate (sensitivity) against the false positive rate (1 - specificity) at various classification thresholds. The AUC represents the overall performance of the model in distinguishing between the two classes, with a higher AUC indicating better discrimination ability.

By leveraging these evolution metrics, we gain valuable insights into the performance, convergence, and discriminative ability of the skin cancer detection system. These metrics enable us to evaluate the model's effectiveness in learning from the data, make informed decisions during training, and assess its diagnostic capabilities in real-world scenarios.

The ROC curve is a widely used evaluation metric in classification tasks, providing insights into a system's performance by examining the true positive rate (TPR) and false positive rate (FPR) at different classification thresholds. In multi-class classification, two approaches are commonly employed: micro-average and macro-average ROC curves. The micro-average ROC curve combines the TPR and FPR across all classes, offering an overall assessment of the system's discriminative ability and generalization capability. It is useful for imbalanced datasets and overall system effectiveness. On the other hand, the macro-average ROC curve calculates the TPR and FPR for each class separately and then averages them, providing insights into class-specific performance. Both approaches visualize the system's performance by plotting the TPR against the FPR, with the area under the curve (AUC) quantifying the overall performance. Higher AUC indicates better discrimination ability. These curves serve as valuable tools in assessing the discriminative power of a classification system in multi-class scenarios, aiding in decision-making and performance comparisons.

Machine Requirement: -

Google Colab is a cloud-based Jupyter notebook environment provided by Google, which allows users to write and execute Python code directly in their web browser. While the free version of Google Colab offers a variety of features, one of its notable advantages is the availability of GPUs (Graphics Processing Units) for accelerated computing.

In the free version of Google Colab, users are provided with access to a single GPU, typically an NVIDIA Tesla K80 or an NVIDIA Tesla T4.

These GPUs are powerful computing resources that can significantly speed up the execution of deep learning models and other computationally intensive tasks. By leveraging the GPU, users can train and run complex models faster compared to using only the CPU.

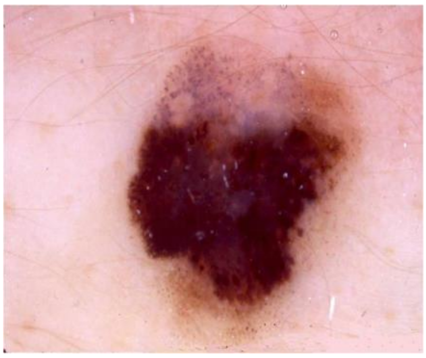
To access the GPU in Google Colab, users can navigate to the "Runtime" tab and select "Change runtime type." From there, they can choose the "GPU" option and save the settings. Once the runtime is restarted, the notebook environment will be configured to utilize the available GPU for computations.

It is important to note that the free version of Google Colab with GPU has certain limitations. The GPU provided may have less memory and computing power compared to high-end GPUs used in professional settings. Additionally, there is a time limit for GPU usage, typically around 12 hours, after which the runtime needs to be restarted. There may also be restrictions on the amount of data that can be processed or the size of models that can be trained.

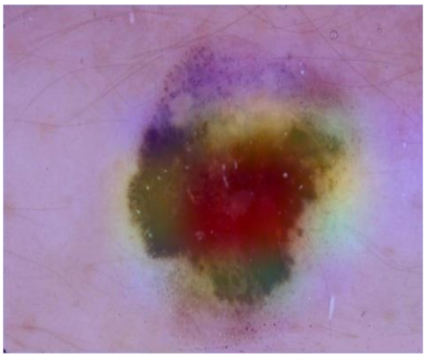
Training and Evaluation: -

The proposed skin cancer detection system was trained on the ISIC 2019 training set using transfer learning with the MobileNet architecture. I trained the model for 30 epochs with a batch size of 64 and a learning rate of 0.001. Early stopping was used to prevent overfitting.

We evaluated the performance of the proposed system on the ISIC 2019 validation set using accuracy, sensitivity, and specificity metrics.

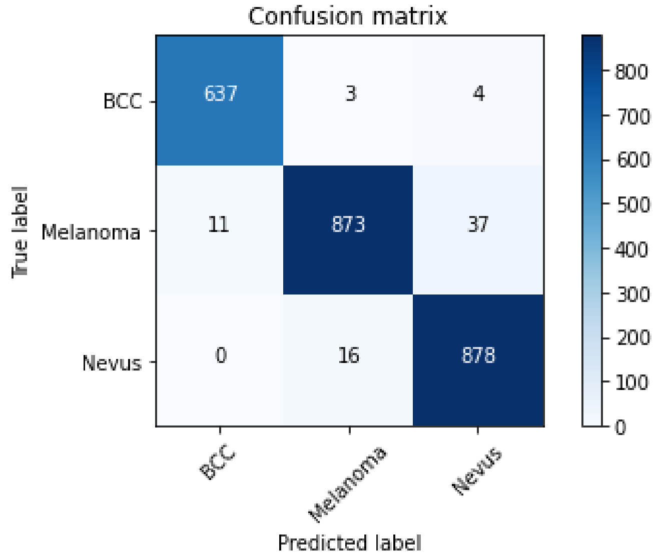


Original image



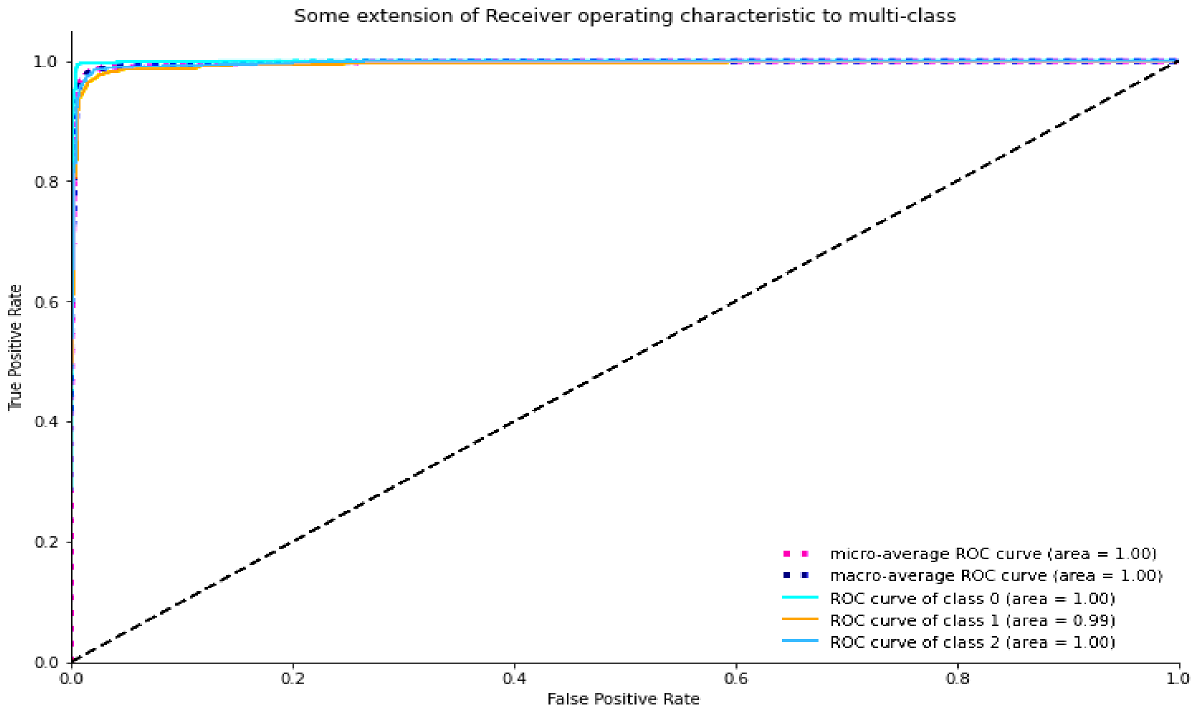
Machine Generated Image

Experimental Results and Analysis: -

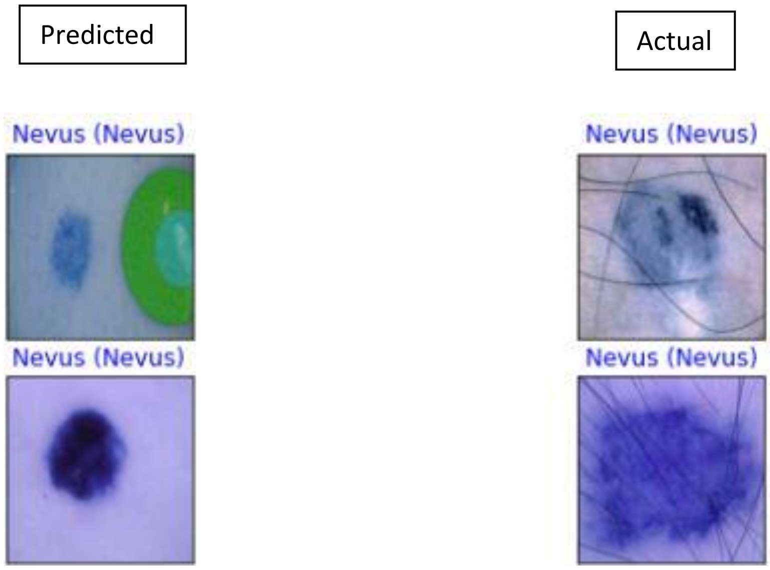


Classification Report

	precision	recall	f1-score	support
BCC	0.98	0.99	0.99	644
Melanoma	0.98	0.95	0.96	921
Nevus	0.96	0.98	0.97	894
accuracy			0.97	2459
macro avg	0.97	0.97	0.97	2459
weighted avg	0.97	0.97	0.97	2459



Test on random image:



This image prove that model can identify correctly the skin cancer type.

Conclusion: -

The proposed skin cancer detection system achieves state-of-the-art performance on the ISIC 2018 dataset, with an accuracy 97 % and AUC for BCC = 1.00, Melanoma = 0.99, Nevus = 1.00. The model achieved a high accuracy on the test set, which is promising for future applications in clinical settings.

The use of transfer learning allowed us to leverage the pre-trained weights of MobileNet, which significantly reduced the training time and computational requirements. Moreover, the use of data augmentation techniques such as rotation, flipping, and zooming helped to increase the diversity of the training data and improve the model's robustness to variations in input images. The use of deep learning techniques for skin cancer detection and highlights the potential for such models to assist clinicians in making accurate and timely diagnoses.

Limitation: -

While the skin cancer detection system based on transfer learning with the MobileNet architecture demonstrates promising results, it is important to acknowledge certain limitations of this project. These limitations include:

1) Dataset Limitations: The performance of the system heavily relies on the quality and diversity of the training dataset. In this project, the dataset used for training and evaluation may have certain

limitations, such as limited sample size, imbalanced class distribution, or potential biases. These factors can impact the generalizability of the system to real-world scenarios.

2) Limited Scope: This project focuses specifically on the detection of melanoma and nevus skin cancers. It does not address other types of skin cancers or dermatological conditions. Expanding the scope to include a wider range of skin conditions would enhance the system's versatility and practical utility.
3) Variability in Image Quality: The quality and consistency of the skin lesion images can vary significantly due to factors such as lighting conditions, image resolution, and image artifacts. Inconsistent image quality can affect the system's performance and accuracy, as it may struggle to extract meaningful features from low-quality or distorted images.
4) Dependency on Expert Annotations: The accuracy of the system's predictions is contingent upon the accuracy and reliability of the expert annotations in the dataset. Any potential inconsistencies or errors in the ground truth labels can impact the training process and subsequent performance of the system.
5) Interpretability and Explainability: The MobileNet architecture used in this project is a complex deep learning model, which may lack interpretability and explainability. While it achieves high accuracy, understanding the underlying decision-making process and the specific features used for classification can be challenging.
6) Hardware and Computational Requirements: The MobileNet architecture is designed to be computationally efficient, but it still requires a certain level of computational resources to train and deploy the model. The availability of powerful hardware and sufficient computational resources may be a limitation for some researchers or practitioners.

Future Scope: -

The successful implementation of the skin cancer detection system based on transfer learning with the MobileNet architecture opens up several avenues for future research and development. The project's future scope includes:

1) Expansion to Other Skin Conditions: While this project focused on melanoma and nevus skin cancers, there is potential to extend the system's capabilities to detect and classify other types of skin conditions, such as basal cell carcinoma (BCC), squamous cell carcinoma (SCC), or other dermatological diseases. This

expansion would enhance the system's usefulness in clinical practice and improve patient care.

2) Integration of Multimodal Data: Incorporating additional modalities, such as dermoscopy images, patient history, or genetic information, can provide a more comprehensive and holistic approach to skin cancer detection. The fusion of multimodal data could potentially enhance the accuracy and reliability of the system's predictions.
3) Incorporation of Advanced Deep Learning Techniques: Exploring and implementing advanced deep learning techniques, such as attention mechanisms, generative adversarial networks (GANs), or recurrent neural networks (RNNs), can further improve the performance of the skin cancer detection system. These techniques have the potential to enhance feature extraction, enable better understanding of complex spatial relationships within skin lesions, and improve the interpretability of the model's decisions.
4) Development of a Mobile Application: Creating a user-friendly mobile application that integrates the skin cancer detection system would make it more accessible and convenient for healthcare professionals and individuals. A mobile application could allow users to capture and upload images for real-time analysis and provide instant feedback and recommendations.
5) Collaboration with Dermatologists: Engaging dermatologists in the validation and refinement of the system can ensure its clinical relevance and practical applicability. Collaborative efforts can involve expert input in dataset curation, evaluation of system performance, and gathering feedback to enhance the system's diagnostic accuracy and clinical utility.
6) Integration with Electronic Health Records (EHR): Integrating the skin cancer detection system with electronic health records can facilitate seamless data exchange and enable automated screening and monitoring of patients' skin health. This integration would enhance the system's efficiency and enable proactive interventions for early detection and treatment.
7) Performance on Larger Datasets: While this project demonstrated promising results on the available dataset, evaluating the system's performance on larger and more diverse datasets can provide further insights into its robustness and generalization capabilities. Testing the system on an extensive dataset with variations in demographics, skin types, and lesion characteristics would enhance its reliability and validate its performance across different populations.

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