Predicting non-melanoma skin cancer via a multi-parameterized artificial neural network

BY

TAPU CHANDRA MALO
ID: 201-15-3317

This Report Presented in Partial Fulfillment of the Requirements for the Degree of Bachelor of Science in Computer Science and Engineering

Supervised By

FABLIHA HAQUE
Lecturer
Department of CSE
Daffodil International University

Co-Supervised By

MS. TANIA KHATUN
Assistant Professor
Department of CSE
Daffodil International University

DAFFODIL INTERNATIONAL UNIVERSITY

DHAKA, BANGLADESH

JANUARY 2024

APPROVAL

This Project/internship titled **"Predicting non-melanoma skin cancer via multi-parameterized artificial neural network"**, submitted by **Tapu Chandra Malo, ID No: 201-15-3317** to the Department of Computer Science and Engineering, Daffodil International University, has been accepted as satisfactory for the partial fulfillment of the requirements for the degree of B.Sc. in Computer Science and Engineering and approved as to its style and contents. The presentation has been held on 22-01-2024.

BOARD OF EXAMINERS

Dr. S. M Aminul Haque (SMAS) — **Chairman**
Professor & Associate Head
Department of CSE
Faculty of Science & Information Technology
Daffodil International University

Md. Sazzadur Ahmed (SZ) — **Internal Examiner**
Assistant professor
Department of CSE
Faculty of Science & Information Technology
Daffodil International University

Amatul Bushra Akhi (ABA) — **Internal Examiner**
Assistant Professor
Department of CSE
Faculty of Science & Information Technology
Daffodil International University

Dr. Md. Sazzadur Rahman (MSR) — **External Examiner**
Professor
Institute of Information Technology
Jahangirnagar University

DECLARATION

I hereby declare that, this project has been done by me under the supervision of **Fabliha Haque, Lecturer, Department of CSE** Daffodil International University. I also declare that neither this project nor any part of this project has been submitted elsewhere for award of any degree or diploma.

Supervised by:

Fabliha 21.01.24

Fabliha Haque
Lecturer
Department of CSE
Daffodil International University

Co-Supervised by:

Tania Khatun

Ms. Tania Khatun
Assistant Professor
Department of CSE
Daffodil International University

Submitted by:

Tapu

Tapu Chandra Malo
ID: -201-15-3317
Department of CSE
Daffodil International University

©Daffodil International University ii

ACKNOWLEDGEMENT

First I express my heartiest thanks and gratefulness to almighty God for His divine blessing makes us possible to complete the final year project/internship successfully.

We really grateful and wish our profound our indebtedness to **Fabliha Haque**, **Lecturer**, Department of CSE Daffodil International University, Dhaka. Deep Knowledge & keen interest of our supervisor in the field of "*Image Processing*" to carry out this project. His endless patience ,scholarly guidance ,continual encouragement , constant and energetic supervision, constructive criticism , valuable advice ,reading many inferior draft and correcting them at all stage have made it possible to complete this project.

We would like to express our heartiest gratitude to **Dr. Sheak Rashed Haider Noori, Professor and Head,** Department of CSE, for his kind help to finish our project and also to other faculty member and the staff of CSE department of Daffodil International University.

We would like to thank our entire course mate in Daffodil International University, who took part in this discuss while completing the course work.

Finally, we must acknowledge with due respect the constant support and patients of our parents.

ABSTRACT

A significant and important part of our life is our health, and integrating computers into our daily lives has the potential to improve our health. Healthcare could undergo a radical change if a machine learning model that can identify a benign or cancerous skin mole from a picture is developed. This paper performs a comprehensive review with an emphasis on the developing body of research on the use of convolutional neural networks (CNNs) to classify skin lesions. The focus is on classifiers that are especially made for skin lesions; techniques that use CNNs only for segmentation or classification of thermoscopic patterns are not included. The paper explores the difficulties in comparing various processes and discusses the issues that need to be resolved in other studies. The implementation uses the Python programming language and a CNN model in Keras with TensorFlow as the backend. ISIC databases that are open to the public are used for training and testing in this research, which is carried out on the Kaggle platform. The collection consists of balanced photos of skin moles that are either benign or cancerous, arranged into two files. Owing to the magnitude of the dataset, only 100% of the total training data is designated for testing when the training and test sets are combined. Seven percent of the dataset is reserved for validation. Various CNN architectures, such as MobileNetv2, efficientNet, and RandomForestClassifier, are employed for analysis. Notably, RandomForestClassifier exhibits the highest accuracy in this scenario. The selected best model undergoes an ablation study based on hyperparameters, with RandomForestClassifier achieving exemplary results: Train Accuracy of 99% and Test Accuracy of 98.37%.

TABLE OF CONTENTS

LIST OF FIGURES

LIST OF TABLES

CHAPTER 1

INTRODUCTION

1.1 Introduction

Among the various types of cancers, skin cancer is often the least discussed. However, in America alone, 5 million cases of skin cancer are reported every year, and the global incidence is several times higher. It is crucial to note that these figures are subject to change, and the prevalence of skin cancer remains a significant ongoing public health concern. Regular updates and awareness efforts are essential to address the impact of skin cancer and implement preventive measures on a broader scale. Convolutional neural networks (CNNs) are a subset of deep neural networks that are commonly used in deep learning for the analysis of visual mental imagery Convolutional systems are inspired by natural forms. here, the features of the neurons are arranged to reflect the range of the species. CNN's main advantage above its predecessors is its ability to recognize important opportunities on its own without assistance from a human.Convolutional neural networks, such as those found in MobileNetv2, efficientNet, and RandomForestClassifier, are Deep Learning algorithmic programs that can recognize and distinguish between different objects in an image by absorbing the image and assigning weights and biases to various aspects of the image. In the past, physicians have been using their oculus to diagnose cancer. However, people make mistakes and this leads to incorrect detection on multiple instances. Even consultants struggle to explain it, especially when the cancer is still in its really early stages. Many hours of work have been published in the field of cancer classification using deep learning and computer vision approaches. These studies employ a wide range of techniques, such as classification alone, segmentation and detection, image processing using various filter types, etc. (Esteva and others, 2017) AdaBoost was utilized on an individual basis to categorize skin lesions. (Xu et al., 2014) used totally different sets of options together with kind of lesion, texture, color etc and neural networks for the creating of a strong diagnosing system. In this study, we developed a system that accurately detects skin cancer and provides us with dataset accuracy. We use Kaggle to execute this procedure. An introduction is given in section one, followed by sections on method and material in section two, results and analysis in section three, and a conclusion and future work in section four.

1.2 Motivation

Familial Impact: Witnessing the impact of this specific cancer on family members underscore the need for improved diagnostic tools. The goal is not only to understand the intricacies of the disease but to actively contribute towards developing solutions that can positively influence patient outcomes.

Inadequacies in Current Practices: The realization that current diagnostic methods may not always catch non-melanoma skin cancer in its early stages, necessitating a more robust and objective approach.

Personal Quest for Information: This research journey is not just a scientific endeavor but a means to empower oneself and others with valuable insights into identifying and diagnosing non-melanoma skin cancer.

1.3 Rational of this study

The goal of researching non-melanoma skin cancer is to address the rising prevalence of these tumors and the difficulties in early identification that go along with them. The accuracy and effectiveness of the traditional detection methods, which mostly rely on visual inspection, are limited.

The objective of this research is to augment the current corpus of knowledge by investigating novel methodologies, with a specific emphasis on technological developments. Using artificial intelligence—more especially, artificial neural networks—offers a viable way to increase diagnostic precision and shorten identification times. Through the use of a multi-parameterized strategy that incorporates several aspects, including picture attributes and patient characteristics, the research endeavors to improve the accuracy of non-melanoma skin cancer prognosis.

1.4 Research Questions

- Can deep learning be used to improve the accuracy of skin cancer detection in humans?
- In contrast to more traditional machine learning methods, how successful is a deep learning-based system for detecting skin cancer?
- Does applying deep learning reduce the amount of annotated data required to train the model?
- How does the addition of clinical data to imaging data affect the efficacy of a deep learning-based skin cancer detection system?
- Is it feasible to use a deep learning-based system for skin cancer detection in a clinical setting to enhance therapy and early diagnosis?

1.5 Expected Output

Detect Non-melanoma skin cancer is our initial goa1.Then Image dataset processed to yield optimal image output Based on their performance, the top deep learning model was chosen ,an analysis of ablation using the top-performing model Performance comparison with the prior model . At last, the best model that was produced .So In the future, we try to develop a program that can detect skin cancer in the very early stage and offer prompt, efficient treatment use with technology.

1.6 Project Management and Finance

Project Management

Project management for skin cancer prediction is a methodical process that starts with identifying goals and stakeholders, then moves on to scheduling resources and deadlines. Curating a diverse dataset is a necessary step in the preparation and collecting of data, and choosing appropriate methods and optimizing parameters are steps in the construction of a model. Validation and testing analyze model performance, leading to deployment and integration into healthcare systems. Constant upkeep, recordkeeping, and monitoring guarantee ongoing efficacy, while ethical considerations direct appropriate utilization. The goal of this thorough approach is to develop a skin cancer prediction model that is both clinically relevant and dependable.

Finance

Data collection, processing power, expertise, software and tools, testing and validation, infrastructure and deployment, deployment and ethical considerations, continuous updates and monitoring, documentation, and post-implementation support are some of the factors that affect how much it costs to develop a skin cancer prediction model. Purchasing or licensing data may be necessary to obtain high-quality and diverse datasets, and training deep learning models may need a substantial amount of processing power, possibly requiring the use of specialized hardware or cloud services. The usage of specialized tools and development frameworks, as well as the hiring of knowledgeable specialists in machine learning and data science, add to the overall cost. Validation, testing, adherence to legal and ethical requirements, deployment, continuous observation, and documentation all result in additional costs. The total cost also includes prospective model changes and post-implementation maintenance. various variations depending on the intricacy of the project, the need for customization, and the strategies selected, including outsourcing or making use of current resources.

1.7 Report Layout

This thesis is organized as follows:

Chapter-1: Introduction: The introduction, research motivation, research purpose, and research question are the subjects covered in this chapter. This chapter is a summary of the study.

Chapter-2: Background Study: This chapter will cover a variety of relevant themes, including the scope of work needed to address the issue and the difficulties in diagnosing the condition at an early stage.

Chapter-3: Research Methodology: This chapter will describe the data collection, preprocessing, and model development process, including details of the chosen.

Chapter-4: Experimental Results and Discussion: This chapter will present the results of the experiments, including the performance of each model on various evaluation metrics.

Chapter-5: Impact on Society, Environment and Sustainability: This chapter describes the detail impact of the research on society, environment and sustainability.

Chapter-6: Summary, Conclusion, Recommendation and Implication for Future Research: This chapter will provide an overview of the study, point out its shortcomings, and suggest future lines of inquiry for ML and DL-based early-stage diabetes prediction research.

CHAPTER 2

Background

2.1 Preliminaries

Skin Cancer: Melanoma, squamous cell carcinoma, and basal cell carcinoma are three types of skin cancer that arise from skin cells. They vary in severity and each has unique features.

Computer Vision: This area of computer science is concerned with creating models and algorithms that can comprehend and evaluate visual data, such as pictures and movies.

Deep Learning: Deep learning is a branch of machine learning that uses multilayer neural networks to identify complex patterns and representations in data.

Convolutional Neural Networks (CNNs) are a particular kind of deep learning network that are particularly good at processing images. Convolutional layers are used to extract characteristics from the images so that these networks can be trained to recognize objects and patterns in pictures.

Random Forest Classification: During training, an ensemble machine learning technique called Random Forest classification creates a large number of decision trees. It produces the mean prediction for regression tasks and the mode of the classes for classification tasks.

2.2 Related Work

In a Stanford study [8], researchers retrained Inception v3 with photographs of skin lesions annotated thermoscopic images by the use of transfer learning. For example, the CNN obtained an overall accuracy of 72.1 ± 0.9% in a three-class disease classification validation, while two dermatologists obtained 65.56% and 66.0% accuracy on a subset of the validation set [8]. The CNN outperformed dermatologists with an accuracy of 55.4 ± 1.7% in a nine-way classification, while their respective accuracies were 53.3% and 55.0%. Additionally, binary disease comparisons were performed in the study, and the results were shown in ROC curves.

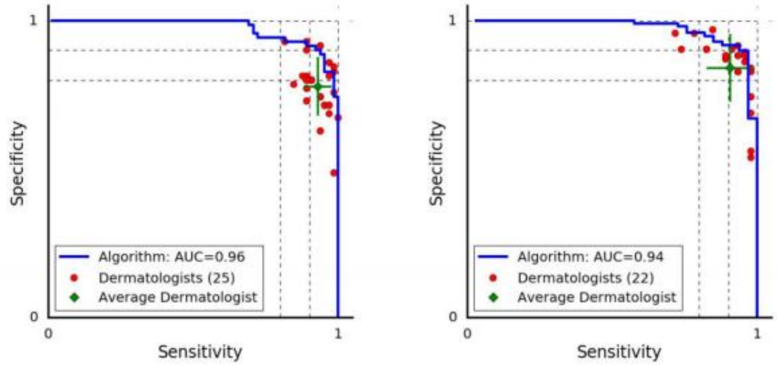

Figure 1:Shows two of the graphs from this analysis

ROC curves produced from the results obtained by [8] are shown in Figure 4. The ROC curve for their test set, which consists of 70 keratosis and 65 cancer pictures, is shown in the left graph. The ROC curve on the right represents their test set, which includes 97 mole photos and 33 skin cancer images. A research by Nylund [29] offered a similar outcome. Nylund used AlexNet, a traditional convolutional neural network, in that investigation [29]. For a 23-way classification, the overall accuracy attained was 55.0%, which is quite similar to the outcomes of the 9-way classification carried out by [8]. Nylund came to the conclusion that, when it comes to binary classification accuracy with little pre-processing and calibration, convolutional neural networks perform on par with dermatologists in practice and cutting-edge machine learning techniques [29].

In order to detect melanoma, a CNN was trained using Google Inception v3 in the study done by Ridell and Spett [30]. The study investigated the impact of training dataset size on the accuracy of melanoma and benign mole classification. Accuracy levels ranged from 70.8% to 77.5% across a range of image sizes evaluated, from 200 to 1600. The inference made was that a larger dataset seems to increase accuracy [30].
The term "skin cancer" encompasses a group of related conditions characterized by uncontrolled cell division and the spread of cells into adjacent tissues [11]. Carcinoma, the most prevalent type of cancer, poses significant dangers, often initiated by exposure to ultraviolet radiation from the sun, which damages the DNA in skin cells. This damage triggers mutations that lead to the uncontrolled proliferation of skin cells, resulting in the

development of cancers. Genetic flaws may also contribute to the onset of cancer. Skin cancer is categorized into various types, including malignancies of basal and epithelial cells, with the latter being particularly perilous [14]. Tumors affecting basal and epithelial cells typically remain localized at the site of origin [7].

While skin cancer represents only a fraction of all skin cancers, it is responsible for a staggering 75% of carcinoma-related deaths [14]. This form of cancer is notably aggressive, often spreading to nearby tissues [7]. Early detection of skin cancer is crucial, with the estimated 5-year survival rate dropping from over 99% when detected in its earliest stages to approximately 14% in its advanced stages [8]. Presently, diagnoses of skin cancer rely heavily on visual assessments. Initial clinical screenings are conducted, followed by dermoscopic analysis, diagnostic testing, and histopathological examinations [15].

2.3 Comparative Analysis and Summary

Table 2.3 summarizes a thorough review of studies on diabetes prediction, including the machine learning and deep learning models used and their maximum levels of accuracy.

SL No	Author Name	Used Algorithm	Best Accuracy with Algorithm
1	Kawahara J	Multi-tract CNN	75.1%(Multi-tract CNN)
2	Esteva A et al	CNN ,CNN-PA	72.1% (CNN-PA)
3	M. A. A. Milton	InceptionResnetV2 PNASNet-5-Large SENet154 InceptionV4	76.0 %(PNASNet-5-Large)
4	Saket S. Chaturvedi	MobileNet	95.84%(MobileNet)
5	Current Study	MobileNetv2, efficientNet, and RandomForestClassifier	98.37%(RandomForestClassifier)

Table 2.3. Comparative analysis with previous work

2.4 Scope of the problem

The Scope of the problem address the following topics:

Enhanced Predictive Models: The research may focus on improving the accuracy and reliability of predictive models for non-melanoma skin cancer. The multi-parameterized artificial neural network suggests an approach that considers various factors or features in the prediction process.

Early Detection: Skin cancer, especially non-melanoma types, benefits significantly from early detection. The research may emphasize the importance of developing models that can identify potential skin cancer cases at an early stage, improving treatment outcomes.

Integration of Multiple Parameters: The term "multi-parameterized" suggests the incorporation of various factors or characteristics in the predictive model. This could include diverse features such as image-based data, patient history, genetic information, and other relevant parameters, aiming for a more holistic prediction approach.

Technological Advances: The use of artificial neural networks indicates a reliance on advanced machine learning techniques. The paper may explore how cutting-edge technologies contribute to the improvement of skin cancer prediction and diagnosis

2.5 Challenges

Data Accessibility and Quality: Comprehensive research on skin cancer may be hampered by insufficient and inconsistent data as well as restricted access to varied databases.

Interpretability of Neural Networks: Understanding and interpreting the features that go into skin cancer predictions is difficult due to the intricacy of artificial neural networks.

Ethical Considerations: addressing moral concerns about potential biases in the data used to train predictive models, informed consent, and patient privacy.

Human-Computer Interaction: assessing dermatologists' use of and confidence in predictive models, as well as any possible opposition or mistrust towards the use of AI-assisted diagnostic tools.

Validation and External Testing: extensive external testing and validation of predictive models on separate datasets to verify the validity and generalizability of the findings.

Real-Time Implementation: Creating strategies to apply predictive models in real-time to healthcare environments so that decisions can be made quickly.
Cost and Accessibility: addressing the costs and issues of accessibility associated with the use of cutting-edge technologies in healthcare settings.

CHAPTER 3

Dataset & Preprocessing

3.1 Research Subject and Instrumentation

The purpose of this part is to provide a thorough explanation of our research techniques. The study's dataset was obtained over the internet in the Kaggle. In an effort to perform our investigation, we tried using Windows as our operating system for our research. We made use of Google's Collab notebooks also Kaggle, a flexible tool built on top of the Python programming language. Users can execute certain programs directly in their web browsers with Collab and Kaggle. GPU and other processing resource utilization is free with Collab and Kaggle.

3.2 Data Collection Procedure

The study's image collection is drawn from several distinct open-access sources. 9605 images were obtained from the ISIC Dermoscopic Archive. The two class malignant contains 4605 images, benign holds 5000 images The grayscale system for each image in the datasets is 224 x 244 pixels. The dataset has been collected from openly accessible website Kaggle.

3.3 Statistical Analysis

The dataset is thoroughly described statistically, as seen in Table 3.1.

Title	**Description**
Total Images	9605
Image Dimensions	224 x 244
Color Gradings	RGB
Data Formats	JPG
Malignant’s	4605
Benign’s	5000

Table 3.1 Dataset Properties

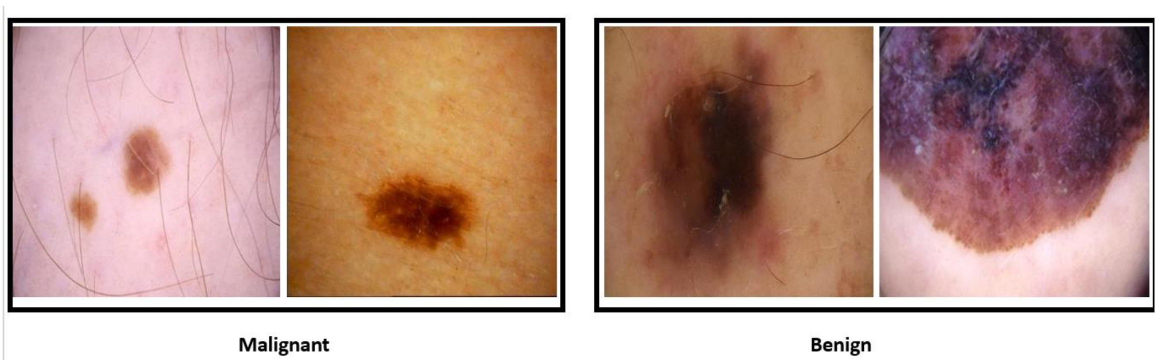

Figure 3.2: Classes of Image

The research includes looking at and analyzing the filtered dataset's statistical properties. Through the disclosure of significant information regarding the dataset's movement, variation, and connections, this study aims to lay the foundation for understanding the basic patterns associated with benign and malignant skin conditions. To characterize the movement of pixel values across the images, one can compute common statistical measures like mean, standard deviation, and other quantiles. This inquiry makes it easy to find likely trends or variances specific to each group. Analyses or tests for statistical significance can also be performed to assess the significance of differences between classes. These techniques might offer significant new perspectives on the ability of particular features to differentiate. It is imperative that you perform statistical analysis in this section to gain a deeper understanding of the composition and characteristics of the dataset. Later on in the research phase, this will assist you in making well-informed decisions on the selection of models, classroom instruction, and assessment.

3.4 Proposed Methodology

I import multiple functions in this project: Sequential from matplotlib import pyplot as plt, os, gc, np, sns, pd, plt, and from keras.models import Sequential. We also import functions from tensorflow, keras.layers, keras.applications, sklearn.model_selection, and keras.preprocessing.image. With 1800 benign labeled samples and 1497 malignant labeled samples, the train set has a size of 2637, and the test set has a size of 660. We also establish the file path for each image. Every image's file path is saved by us.

Following the division of the dataset into various classes, the pictures are loaded into RAM. The new train set has the shape (2818, 224, 224, 3), the new test set has the shape (330, 224, 224, 3), and the validation set has the shape (149, 224, 224, 3).

The data is then generated, yielding a fresh total of 5636 training samples. The training data's values have been normalized, and its current shape is (5636, 224, 224, 3). The minimum and maximum values are, respectively, 0.0 and 1.0.

The subsequent step involves building and training the model. A CNN model is constructed using Keras, and the details are presented in the table below.

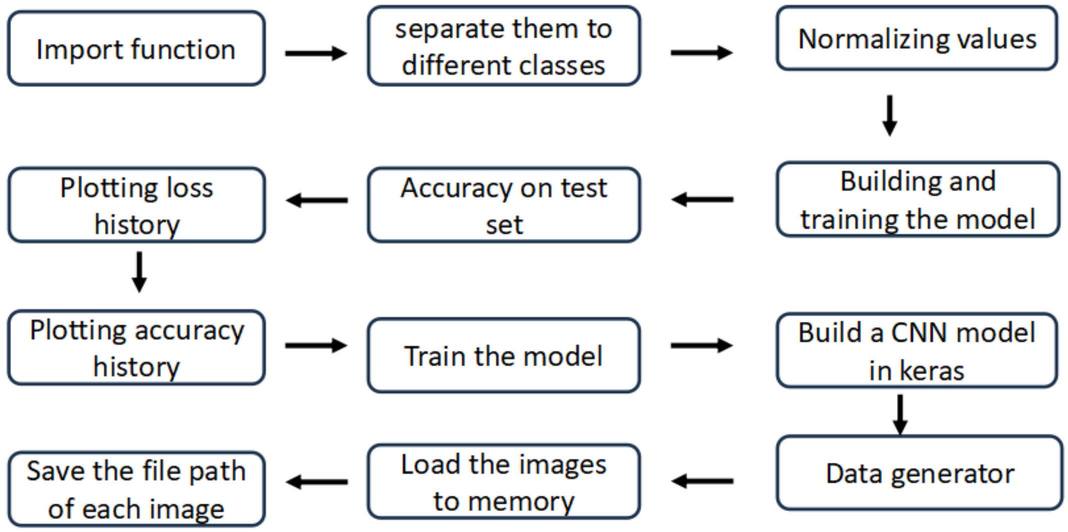

Figure 3.4.1: Full system block diagram showing the process by which the system accomplishes pick and place activity.

MobileNetv2

A GoogleAI model called MobileNet is particularly suited for real-time categorization on-device (not to be confused with Single Shot Detector, MobileNetSSD). This implementation makes use of ImageNet's transfer learning for your dataset.

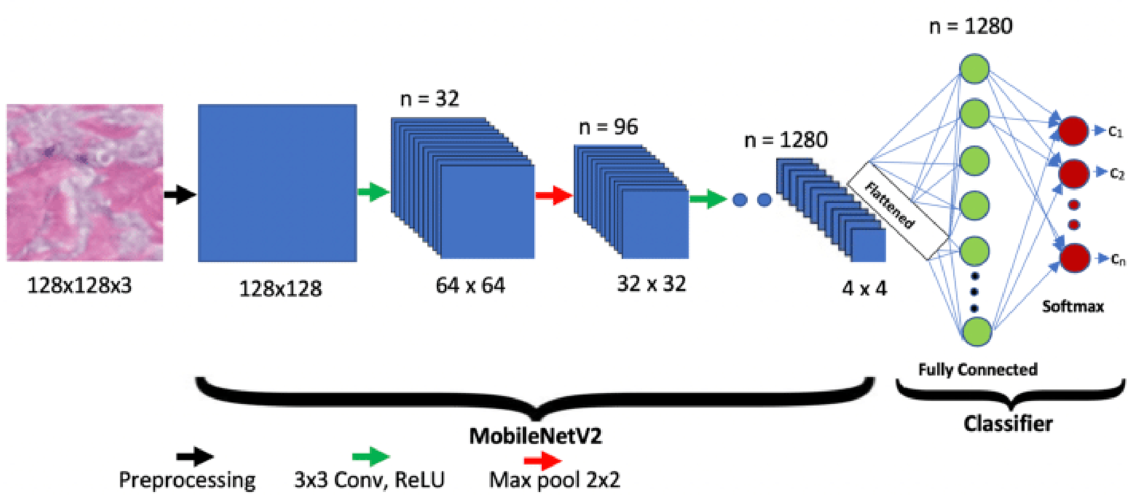

Figure 3.4.2: MobileNetV2 Process

EfficientNet

Using a compound coefficient, EfficientNet is a convolutional neural network design and scaling technique that uniformly scales all dimensions of depth, breadth, and resolution.

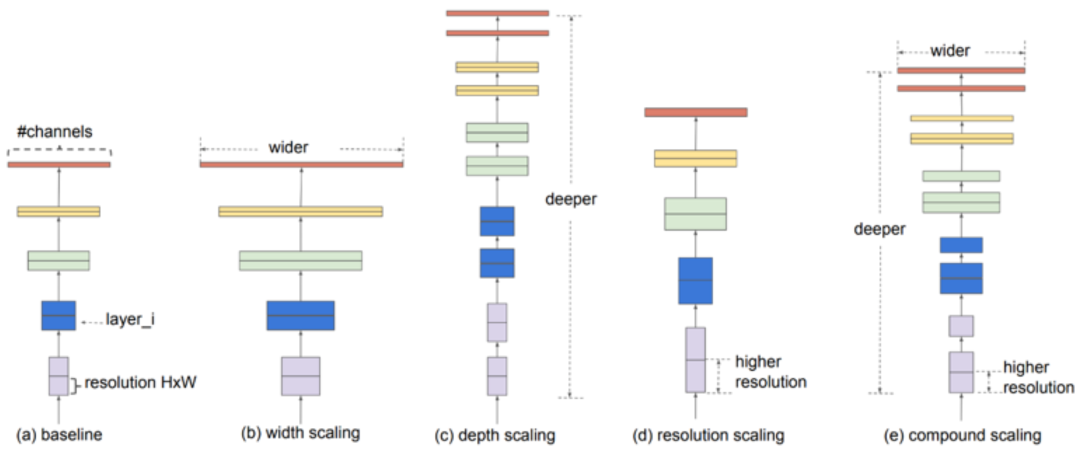

Figure 3.4.3 Model Scaling(a) Baseline network (b)Width scaling (c)Depth scaling(d) Resolution. (e) compound scaling

RandomForestClassifier

How should an image be classified using random forests?

1. Load the image of the digits.
2. Extract the training and testing datasets from the image.
3. Construct a decision tree from scratch.
4. Access the default settings for the parameters.
5. Train the decision tree.
6. Ascertain the testing data's target labels....
7. Calculate and report the attained accuracy.

3.5 Implementation Requirements

I implement in those Model MobileNetv2, efficientNet, and RandomForestClassifier .and there are Out among all of them, our RandomForestClassifier score was the highest at 98.37% .

3.5.1 Proposed Model (RandomForestClassifier)

Random Forest is a powerful ensemble learning technique that is often used for classification and regression applications. To improve accuracy and durability, it builds several decision trees during training and merges their predictions.. For every tree, random subsets of data and characteristics are selected in order to reduce overfitting. The approach handles large datasets, high-dimensional spaces, and nonlinear interactions with skill. In scikit-learn, using RandomForestClassifier typically involves initializing the classifier, fitting it to the training data, and then using the trained model for predictions. I can also adjust hyperparameters such as the number of trees, depth of trees, and the criteria for splitting nodes to fine-tune the model's performance.

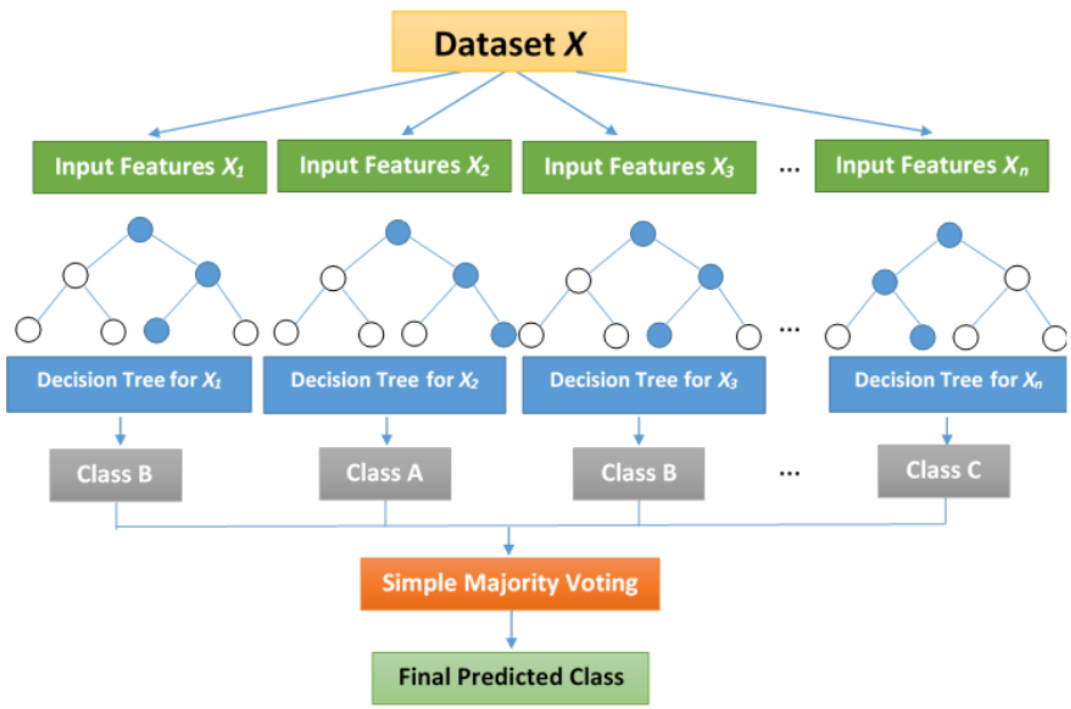

Figure 3.5.1: RandomForestClassifier process

Confusion Matrix

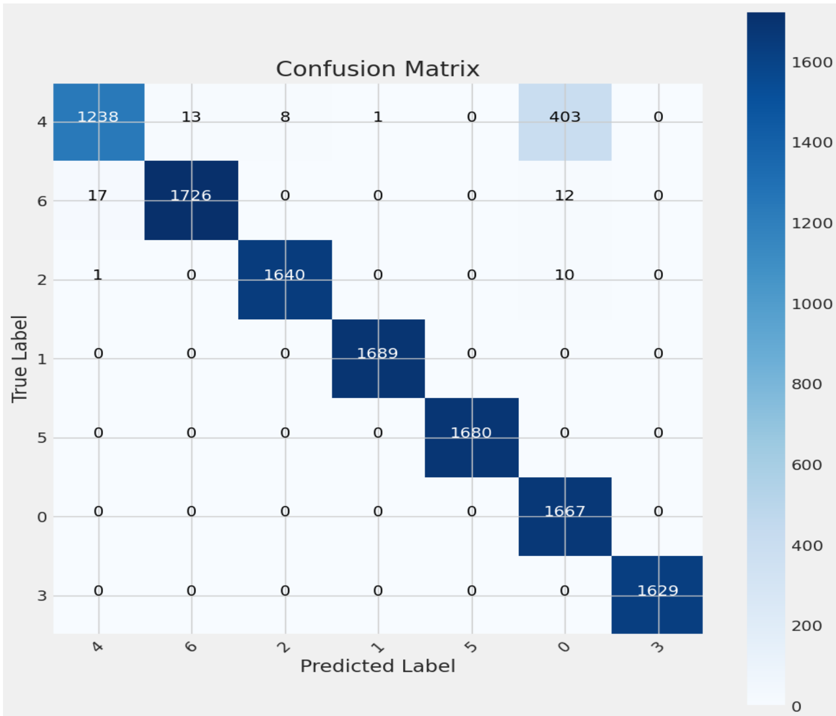

Figure 3.5.2: Confusion Matrix

Advantages of Skin Cancer Prediction:

High Accuracy: RandomForest's ensemble technique generates accurate forecasts by discovering intricate relationships within the data.

Robustness: RandomForest adds diversity and prevents overfitting by using different feature and data subsets for each tree.

Feature Importance: The algorithm assists in identifying the critical factors influencing the projections of cardiovascular health by producing insights into the relevance of features.

Managing Missing Data: It effectively handles missing values, ensuring that incomplete data does not significantly affect the model's

CHAPTER 4

Research Methodology

4.1 Experimental Setup

Using real data, I analyze the impact of the last step in the application. With my estimations, I am able to get a performance that is rather accurate. Approximately 9605 photos were used in my research. Every dataset yielded two extracted classes. This implies that I gathered data from Kaggle. The data was then trained using the machine learning tool in Kaggle and Google colab.

4.2 Experimental Results & Analysis

MobileNetv2:

After epoch 20 I get Accuracy: 95.11%

EfficientNet:

Figure 4.2.1: EfficientNet train ,test loss & accuracy

Test Loss: 0.49761962890625
Test Accuracy: 87.5%

RandomForestClassifier :

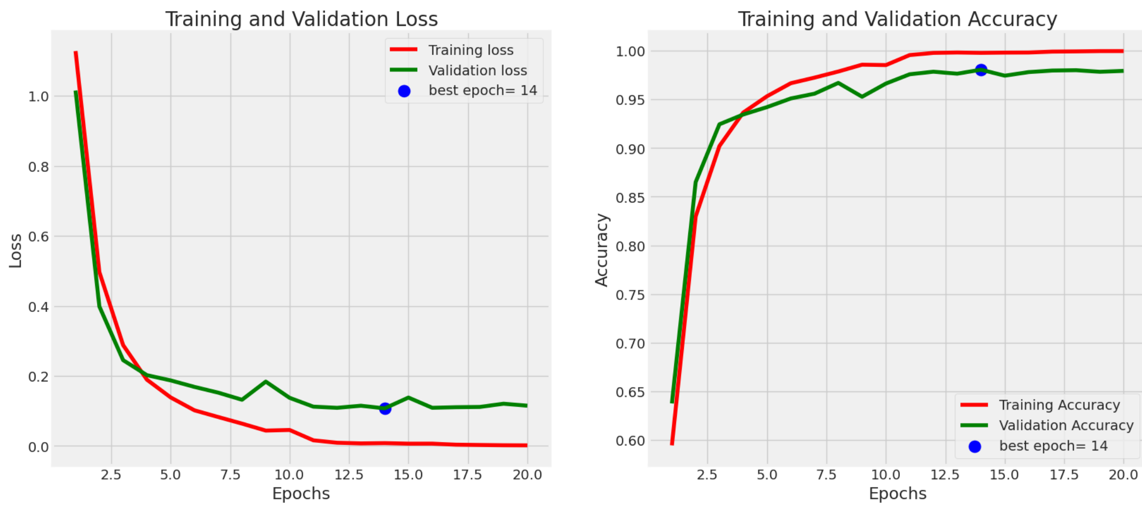

Figure 4.2.2: RandomForestClassifier train ,test loss & accuracy

Train Loss: 0.00091
Train Accuracy: 0.99
Test Loss: 0.082
Test Accuracy: 98.37%

5.2.3 Performing Analysis of Best Model

RandomForestClassifier is the best Performing Analysis with Test Accuracy: 98.37%

5.2.4 Comparison of Exiting work

Model	**ACC**	**Epoch**	**Dataset**
MobileNetv2	95.11%	20	skin-cancer-mnist-ham10000
EfficientNet	87.5%	20	skin-cancer-mnist-ham10000
RandomForestClassifier	98.37%	20	skin-cancer-mnist-ham10000

Table 5.2: Comparison Table

4.3 Discussion

Here I am use CNN based with 3 Models then find the best model out of them and That is 98.37%.In future I try to implement more model with based on computer technologies and techniques.

CHAPTER 5

Impact on Society, Environment and Sustainability

5.1 Impact on Society

Every nation beset by issues such as a high proportion of the populace lacking the means to seek medical assistance, which is exacerbated by the lack of medical specialists intercountry. Access to healthcare is therefore still quite difficult, especially in the case of heart disease. It affects a large percentage of the population, yet access to care is hampered by lack of resources and a shortage of medical professionals. However, our developed approach reliably and accurately detects heart problems. Our method, which is entirely computerized, generates diagnoses rapidly and with little waiting. Identifying and quickly diagnosing skin issues is made possible by identifiable symptoms. Our approach demonstrates economic viability using machine-driven diagnoses similar to those made by specialty clinicians. Since the procedures and tests are free, those who have previously been unable to pay for or make time for medical evaluations can now access them. Our method improves society and reduces death rates by helping people recognize skin issue and get adequate healthcare without having to spend money for clinical tests.

5.2 Impact on Environment

For our study, we consulted patient data from sources connected to healthcare. Datamining techniques are employed by our technology to assess this data in order tofacilitate healthcare decision-making. Clinical decision-making supported by computer- based patient data may enhance patient outcomes and safety, lessen needless practicedisparities, and cut down on medical procedure errors. Data mining is a potent modelingand analysis tool that improves the quality of expert judgments and the knowledge base. This computerized approach replaces traditional methods that relied on clinicians' experience and intuition to guide their therapeutic decisions. Additionally, it increases knowledge of risk factors such water tainted by arsenic, occupational hazards for restaurant workers, and air pollution, offering insights into environmental factors that lead to heart disease.
©Daffodil International University 33

5.3 Ethical Aspects

Throughout this undertaking, there are a few ethical considerations that we must bear in mind. since there is a great deal of personal information at risk. Because of this, we have a moral obligation to protect their privacy. Remember that the study guarantees the protection of personal data and upholds strict security measures, placing a strong focus on patient safety. It does not exhibit genetic bias or any other form of discrimination. The purpose of the study design is objectivity, and the researchers accept full responsibility for the investigation's conclusions.

5.4 Sustainability

Plan In our research, we were capable of to obtain nearly perfect accuracy. Obtaining medical care is hampered by numerous factors in our nation. Neither money nor doctors are available to us. Rapid diagnosis is possible thanks to our automated technology, which also removes the necessity for clinical evaluation. Individuals would therefore greatly benefit from our project if we could make it available to them.

CHAPTER 6

Summary, Conclusion & Future Work

6.1 Summary of the Study

Principal Findings One issue with the comparison of skin lesion classification strategies is that the thought-about downside formulations of the individual works take issue, typically solely slightly. this happens not just for the thought-about coaching categories and therefore the used knowledge, however conjointly for the given applied math quantities. additionally, some works use private archives of skin clinics additionally to in public accessible knowledge archives [16,17]. This makes it even harder to breed the results. Since 2016, the ISIC skin cancer Project has tried to boost this facet by establishing a in public accessible archive of dermatoscopic skin lesion pictures as a benchmark for education and analysis [18]. additionally, they declared associate annual challenge during which a clearly outlined downside should be addressed . it'd be fascinating if additional work would compare itself with this benchmark to realize a more robust ranking of the procedures within the state of analysis.

6.2 Conclusions

The long-term scope or application of this strategy is covered in this chapter. Because our system may be web-based, different types of additional options may be added to the existing system based on the needs.

To sum up, this study investigated the potential of deep convolutional neural networks in the differentiation between benign and malignant cancer. Our findings suggest that dermatologists are outclassed by progressive, profound learning styles that are prepared for dermoscopy footage. We have observed that significantly greater symptom accuracy may be achieved by employing highly complex convolutional neural networks with exchange learning and fine-tuning them on dermoscopy images. compared to master physicians and medical professionals. Despite the fact that this paper does not include a preprocessing step, the alpha results are very encouraging. via order to help dermatologists, these models will be functionally available via dermoscopy frameworks or similarly on smartphones. To encourage adaptation, more completely diverse datasets (different classes, various ages) with slightly more dermoscopy film and modified six assessments per lesson are required. To improve the model's accuracy, it will also be beneficial to use all of the information contained in each image.

6.3 Implication for Further Study

The main objective of developing this method is to produce a basic platform for startup clinics and diagnostic centers. The system may be additional improved than the present type. within the context of securing this method any work may be done by together with firewalls and different means that of securing this method. to boot, the interface of the system may be a piece ongoing to appear additional easy. The sign in section may be updated by together with the popular social media sites. once a user desires to sign in for associate degree account it may be created easier by incorporating the thought social media sites like language with one’s Facebook or Twitter profile. the assistance tab may be any increased through a virtual tour within the diagnostic center with the situation of necessary junctions like the chamber space of a selected doctor or a science lab room.There is a possibility that research will continue in an effort to develop a CNN that is more accurate than [8] in differentiating between benign and malignant melanoma. from now on, make the same binary comparisons that were provided in this report. Even more intriguing would be to compare dermatologists' performance to our findings about the differentiation between malignant melanoma and star freckles and keratoses. Furthermore, we were only able to identify two skin lesions that were determined to be Clearly similar to malignant melanoma. Dermatologists are also prepared to recognize other binary comparisons that they might want to test prior to using CNN in an actual clinical situation. An alternate examination would be the kind of inquiry that CNN does for people with different skin tones. In order to determine whether or not all individuals can use the CNN, it might be essential to attempt this.

REFERENCES

[1] T. J.Brinker, Klode J, Esser S, Schadendorf D. Facial-aging app availability in waiting rooms as a potential opportunity for skin cancer prevention. JAMA dermatology 2018;154(9):1085e6.

[2] Schadendorf D, van Akkooi ACJ, Berking C, et al. Melanoma. Lancet 2018;392(10151):971e84.

[3] Brinker TJ, Hekler A, Utikal JS, et al. Skin cancer classification using convolutional neural networks: systematic review. J Med Internet Res 2018;20(10).

[4] L. Bi, J. Kim, E. Ahn, and D. Feng. Automatic skin lesion analysis using large-scale dermoscopy images and deep residual networks. arXiv preprint arXiv:1703.04197, 2017.

[5] N. Codella, V. Rotemberg, P. Tschandl, M. E. Celebi, S. Dusza, D. Gutman, B. Helba, A. Kalloo, K. Liopyris, M. Marchetti, et al. Skin lesion analysis toward melanoma detection 2018: A challenge hosted by the international skin imaging collaboration (isic). arXiv preprint arXiv:1902.03368, 2019.

[6] L. Xu, J. S. Ren, C. Liu, and J. Jia. Deep convolutional neural network for image deconvolution. In Advances in neural information processing systems, pages 1790–1798, 2014.

[7] P. Tschandl, C. Rosendahl, and H. Kittler. The ham10000 dataset, a large collection of multi-source dermatoscopic images of common pigmented skin lesions. Scientific data, 5:180161, 2018.

[8] Szegedy, W. Liu, Y. Jia, P. Sermanet, S. Reed, D. Anguelov, D. Erhan, V. Vanhoucke, and A. Rabinovich. Going deeper with convolutions. In Proceedings of the IEEE conference on computer vision and pattern recognition, pages 1–9, 2015

[9] A. Rezvantalab, H. Safigholi, and S. Karimijeshni. Dermatologist level dermoscopy skin cancer classification using different deep learning convolutional neural networks algorithms. arXiv preprint arXiv:1810.10348, 2018.

[10] V. Pomponiu, H. Nejati, and N.-M. Cheung. Deepmole: Deep neural networks for skin mole lesion classification. In 2016 IEEE International Conference on Image Processing (ICIP), pages 2623–2627. IEEE, 2016.

[11] E. Nasr-Esfahani, S. Samavi, N. Karimi, S. M. R. Soroushmehr, M. H. Jafari, K. Ward, and K. Najarian. Melanoma detection by analysis of clinical images using convolutional neural network. In 2016 38th Annual International Conference of the IEEE Engineering in Medicine and Biology Society (EMBC), pages 1373–1376. IEEE, 2016.

[12] Esteva A, Kuprel B, Novoa RA, Ko J, Swetter SM, Blau HM, et al. Dermatologist-level classification of skin cancer with deep neural networks. Nature 2017 Dec 02;542(7639):115-118.

[13] A. Mahbod, R. Ecker, and I. Ellinger. (Feb. 2017). ''Skin lesion classification using hybrid deep neural networks.'' [Online]. Available:https://arxiv.org/abs/1702.08434v1

[14] K. M. Li and E. C. Li. Skin lesion analysis towards melanoma detection via end-to-end deep learning of convolutional neural networks. CoRR, abs/1807.08332, 2018.

[15] A. Esteva et al., ''Dermatologist-level classification of skin cancer with deep neural networks,'' Nature, vol. 542, no. 7639, pp. 115–118, 2017.

[16] Albahar, M. A., Skin lesion classification using convolutional neural network with novel Regularizer. IEEE Access 7:38306–38313, 2019.

[17] Yu, Z., Ni, D., Chen, S., Qin, J., Li, S., Wang, T., Lei, B.: Hybrid dermoscopy image classification framework based on deep convolutional neural network and fisher vector. In: Biomedical Imaging (ISBI 2017), 2017 IEEE 14th International Symposium on, IEEE (2017) 301–304

[18] Du-Harpur, Xinyi, Callum Arthurs, Clarisse Ganier, Rick Woolf, Zainab Laftah, Manpreet Lakhan, Amr Salam et al. "Clinically-relevant vulnerabilities of deep machine learning systems for skin cancer diagnosis." The Journal of Investigative Dermatology (2020).

[19] Phillips M, Marsden H, Jaffe W, Matin RN, Wali GN, Greenhalgh J, et al. Assessment of Accuracy of an Artificial Intelligence Algorithm to Detect Melanoma in Images of Skin Lesions. JAMA Netw Open. 2019;2(10):e1913436

[20] Kawahara J, Hamarneh G. Multi-resolution-Tract CNN with Hybrid Pretrained and Skin-Lesion Trained Layers. In: Wang L, Adeli E, Wang Q, Shi Y, Suk HI (eds) Machine Learning in Medical Imaging. MLMI 2016. Lecture Notes in Computer Science. 2016;10019. https://doi.org/10.1007/978-3-319-47157-0_20

[21] Esteva A et al. Dermatologist-level classification of skin cancer with deep neural networks. Nature. 2017; 542(7639):115–118. https://doi.org/10.1038/nature21056

[22] M. A. A. Milton, "Automated Skin Lesion Classification Using Ensemble of Deep Neural Networks in ISIC 2018: Skin Lesion Analysis Towards Melanoma Detection Challenge," Jan. 2019.

17%	9%	9%	8%
SIMILARITY INDEX	INTERNET SOURCES	PUBLICATIONS	STUDENT PAPERS

PRIMARY SOURCES

1	dspace.daffodilvarsity.edu.bd:8080 Internet Source	3%
2	Dipu Chandra Malo, Md. Mustafizur Rahman, Jahin Mahbub, Mohammad Monirujjaman Khan. "Skin Cancer Detection using Convolutional Neural Network", 2022 IEEE 12th Annual Computing and Communication Workshop and Conference (CCWC), 2022 Publication	3%
3	Submitted to Cornell University Student Paper	1%
4	Submitted to Damonte Ranch High School Student Paper	1%
5	worldwidescience.org Internet Source	1%
6	Submitted to University of Sydney Student Paper	1%