Major Project

On

Skin Cancer/Lesion Classification Using Different Deep Learning Models

Project report submitted in partial fulfilment of the requirement for the degree of

Bachelor of Technology

In

Biomedical Engineering

Submitted By:

Alan Biju (18111006)

Ayush Rai (18111015)

Banoth Naveen Kumar (18111016)

Gaurav Kar (18111025)

Under the Supervision of:

Dr. Bikesh Kumar Singh

DEPARTMENT OF BIOMEDICAL ENGINEERING

NATIONAL INSTITUTE OF TECHNOLOGY RAIPUR

(APRIL 2022)

CERTIFICATE

It is certified that the work contained in the project report titled "**Skin Cancer/Lesion Classification Using Different Deep Learning Models**" by *"Alan Biju (18111006)", "Ayush Rai (18111015)", "Banoth Naveen Kumar (18111016)" & "Gaurav Kar (18111025)"* has been carried out under my supervision and that this work has not been submitted elsewhere for a degree.

....

Dr. Bikesh Kumar Singh

Assistant professor

Department of Biomedical Engineering

National Institute of Technology, Raipur

April 2022

DECLARATION

I declare that this written submission represents my ideas in my own words and where others' ideas or words have been included, I have adequately cited and referenced the original sources. I also declare that I have adhered to all principles of academic honesty and integrity and have not misrepresented or fabricated or falsified any idea/data/fact/source in my submission. I understand that any violation of the above will be cause for disciplinary action by the Institute and can also evoke penal action from the sources which have thus not been properly cited or from whom proper permission has not been taken when needed.

………………………

Alan Biju (18111006)

…………………………

Ayush Rai (18111015)

…………………………

Banoth Naveen Kumar (18111016)

……………………………………

Gaurav Kar (18111025)

ACKNOWLEDGEMENT

Every project big or small is successful largely due to the effort of a number of wonderful people who have always given their valuable advice or lent a helping hand. We sincerely appreciate the inspiration, support and guidance of all those people who have been instrumental in making this project a success. We would like to express our gratitude to the ***Director of NIT Raipur*** for providing us necessary support to execute the project work.

It is a matter of profound privilege and pleasure to extend our sense of respect and deepest gratitude to our project supervisor ***Dr. BIKESH KUMAR SINGH***, Department of Biomedical Engineering under whose precise guidance and gracious encouragement we had the privilege to work and learn.

We avail this opportunity to thank ***Dr. BIKESH KUMAR SINGH***, Head of the Department of Biomedical Engineering, for facilitating such a working and pleasant environment in our department.

Skin Cancer/Lesion Classification Using Different Deep Learning Models

Abstract

As we know "Skin Cancer" is one of the most common cancer in humans, hence we decided to take up this topic to delve further and solve the problem of skin cancer or lesion detection. We all know how advancement in machine learning for the past few decades have improved image classification especially in healthcare hence in this project we decided to use various deep learning methods to implement multi class classification in our chosen skin lesions HAM10000 dataset. We implemented state of the art convolutional neural networks (CNN) such as ResNet-50, VGG16, AB-ResNet-50 (Attention based ResNet-50) and MobileNet for real time use of deep learning algorithm. Our CNN had really good accuracy as well as precision and recall. What we found after reading several deep learning research papers on skin lesion classification is that real time or real life use of deep learning models are very rare, researchers generally implement a deep learning model and focus on accuracy rather than real world use, so we tried to make a real world use case of our deep learning model developing a simple website which consistently give top three predictions of skin lesions

Keywords: ResNet-50 (Residual Networks – 50), Convolutional Neural Networks (CNN), VGG-16, Deep learning, AB-ResNet-50 (Attention based ResNet-50).

Contents

(1) Certificate

(2) Declaration

(3) Acknowledgement

(4) Abstract

(5) Introduction

(6) Dataset Selection

(7) Types of Deep learning models & Methodology

(8) Results

(9) Conclusion

(10) References

List of Tables

Table 5.1: Summary of all Deep learning algorithms

List of Figures

Figure no	**Title**
Fig 2.1	***Skin Lesion Dataset images***
Fig 3.1	***Skin lesion detection architecture design***
Fig 3.2	***The basic architecture of VGG16***
Fig 5.1	***Accuracy of CNN***
Fig 5.2	***Confusion Matrix of CNN***
Fig 5.3	***ROC curve of VGG16***
Fig 5.4	***ROC curve of Res-Net-50***
Fig 5.5	***ROC curve of AB-ResNet-50***
Fig 5.6	***Confusion matrix of MobileNet***
Fig 5.7	***Real time implementation of website screenshot***
Fig 5.8	***Heatmap of our best performing deep learning algorithm: Attention based ResNet-50***
Fig 5.9	***Heatmap comparison of our best performing algorithm AB-ResNet-50 (right) with our first CNN model (left)***

Abbreviations

CNN: Convolutional neural network

VGG16: Visual geometry group 16

ResNet-50: Residual Network 50

AB-ResNet-50: Attention based Residual Network 50

Nv: Melanocytic nevi

Mel: Melanoma

Bkl: Benign keratosis-like lesions

Bcc: Basal cell carcinoma

Akiec: Actinic keratoses

Vasc: Vascular lesions

Df: Dermatofibroma

Table of Content:

1. Introduction
2. Dataset Selection
3. Types of Deep Learning Models & Methodology
4. Members & Contribution
5. Results
6. Conclusion

1. Introduction

Skin cancer is the most common diagnosed cancer in India and worldwide. Skin cancer is a disease that occurs when abnormal cells grow in the skin. Most types of skin cancers are caused by ultraviolet (UV) light, which can damage DNA and cause mutations that lead to uncontrolled growth of new blood vessels and tumours. UV light may also trigger inflammation, which can contribute to skin cancer development. It is caused by abnormal growths or mutations in cells that are called malignant (cancer) cells. These abnormal cells may grow and spread to other parts of the body, causing an increase in size and number of these abnormal cells. This can cause disfigurement, pain, itching, bleeding and infection. Skin cancer is a malignant (cancer) growth on the skin. Like all cancers, it is caused by uncontrolled cell division and can be cured if detected early enough. Skin cancer usually starts as a small growth that may not look abnormal at first. It often appears as a red or brown spot of skin with no hair growing from it. It can occur anywhere on the body, but most often occurs on sun-exposed areas such as the face, ears, neck and hands. Skin cancers are also known as melanoma or cutaneous neoplasms. The most common types of skin cancer are basal cell carcinoma and squamous cell carcinoma. There are many different types of skin cancer: basal cell carcinoma (BCC), squamous cell carcinoma (SCC), melanoma, Merkel cell carcinoma (MCC) and others. The most common form is BCC which accounts for about 90% of all cases. The exact cause of skin cancer is not fully understood. However, there are several factors that may increase your risk of developing this disease: The majority of skin lesions are benign (non-cancerous). However, some types of skin lesions may be life threatening if they spread to other parts of your body or if they cause an infection in your body.

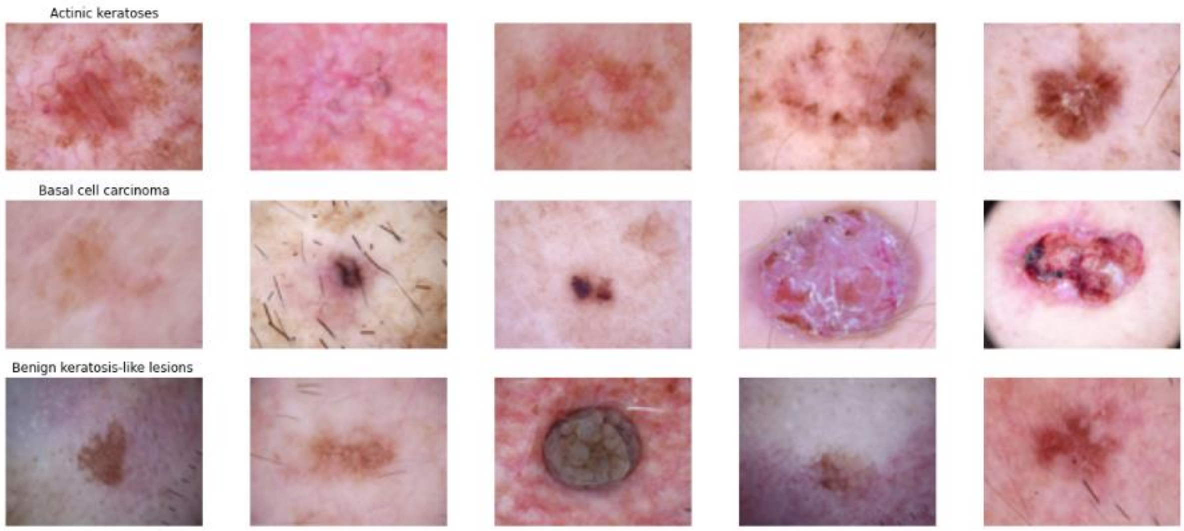
Our task in this project was to select an opensource dataset which has ample number of images to apply state of the art deep learning algorithms. We used various deep learning models such as CNN, VGG16, ResNet-50, MobileNet and a best performing deep learning algorithm with attention based deep learning method in our case it was ResNet-50.

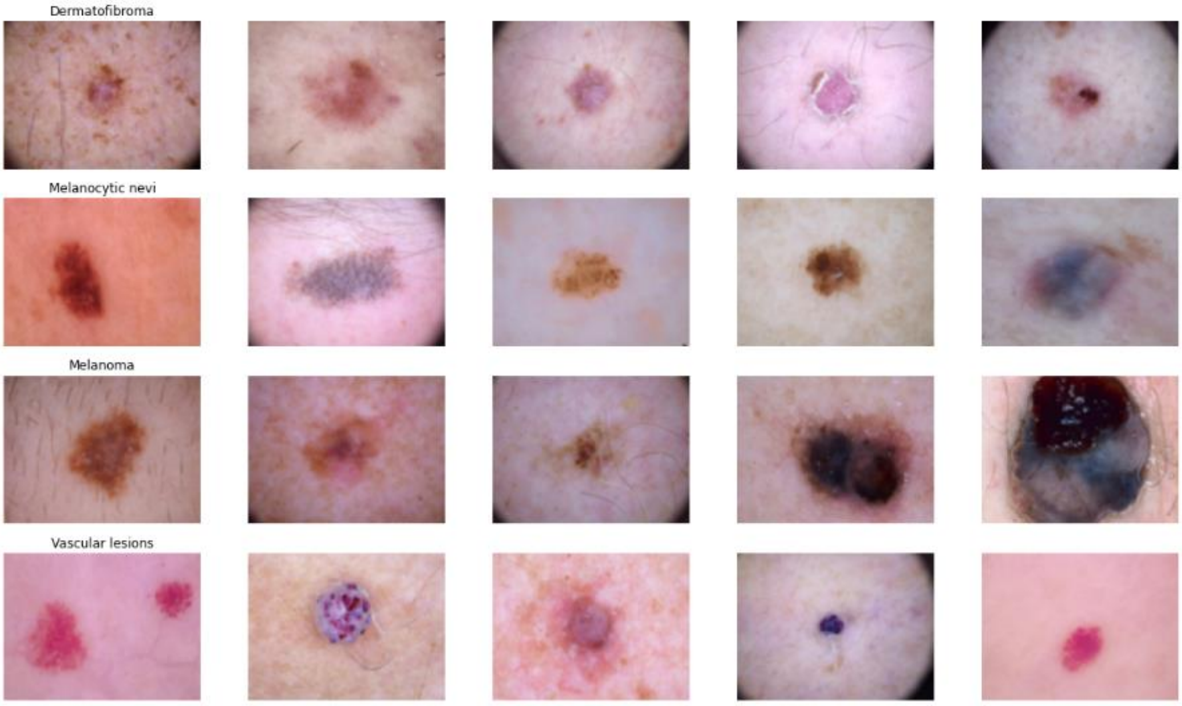
2. Dataset Selection

We chose HAM (10000) dataset which was available on Harvard Dataverse website. The dataset contains two folder which has 5000 images each respectively. Our first task was to combine it and store it in a single folder of 10015 skin lesion images. We used Jupyter notebook provided by google Colab to do all the coding and data processing. The dataset has 10015 images in which seven types of skin lesions are there viz.:

- Melanocytic nevi
- Melanoma
- Benign keratosis-like lesions
- Basal cell carcinoma
- Actinic keratoses
- Vascular lesions
- Dermatofibroma

Fig 2.1: Skin Lesion Dataset images





3. Types of Deep learning models & methodology

Our task in this project was to use state of the art deep learning models and apply it on our HAM (10000) dataset.

We have used various Deep learning algorithms viz.:

- CNN
- VGG16
- ResNet-50
- ResNet-50 with attention based deep learning
- MobileNet with Web implementation

Any deep learning model has the below mentioned process which we used in all of our above-mentioned deep learning models**:**

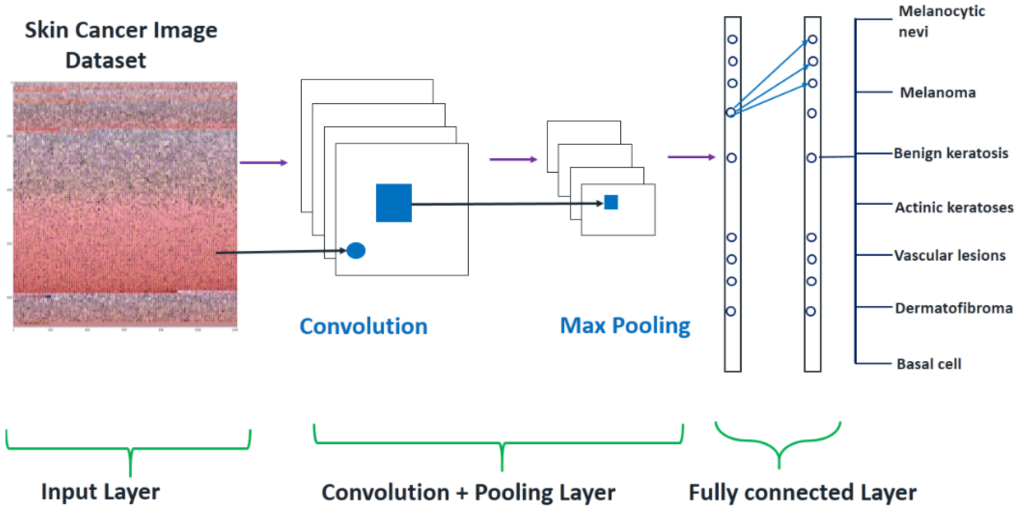
- Dataset Selection
- Importing essential libraries
- Data Cleaning
- Exploratory data analysis (EDA)
- Splitting Dataset (Train & Test sets)
- Deep learning algorithm selection

- Mock data training
- Data Augmentation
- Model Building
- Result

CNN: Convolutional neural network is a type of artificial neural networks that uses convolutions, which are mathematical operations that are used to filter out certain information from an image. In this way, the output of the network can be changed by changing the input data. The main advantage of using convolutional neural networks is that it has a higher capacity for learning compared to other types of artificial intelligence such as recurrent and feed-forward networks. This makes them suitable for analyzing images with high resolution and large datasets.

We first chose to start from scratch with our own implementation of CNN (Convolutional Neural Network). To implement this, we used Keras sequential API, which has thirty-two filters for first two layers (Conv2D layer) and sixty-four filters for the last layers.

Fig 3.1 Skin lesion detection architecture design

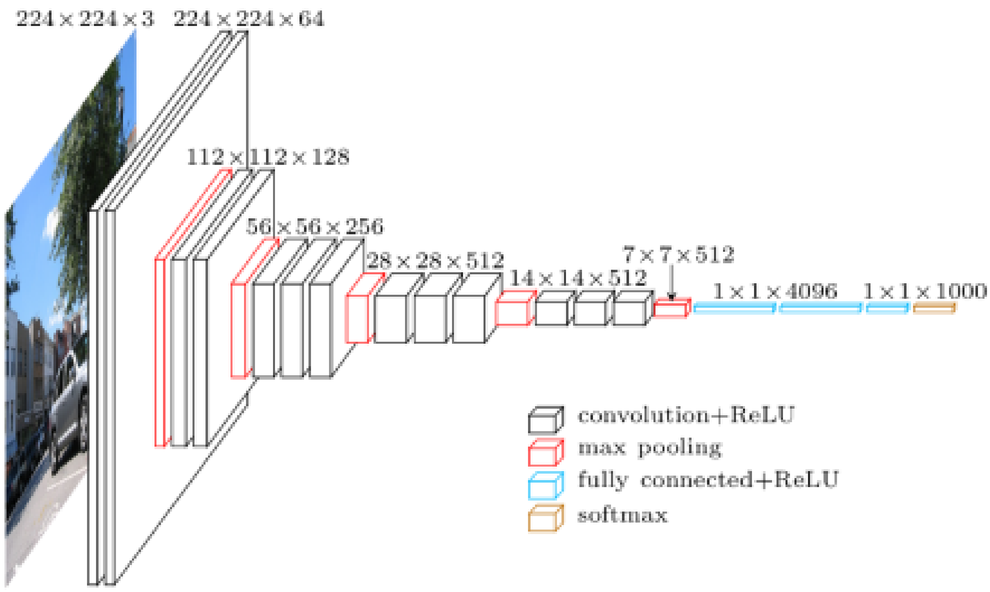


VGG16: VGG16 is a convolutional neural network architecture designed to be used as an end-to-end deep learning model. It can be trained using the TensorFlow framework, and has been optimized for both speed and accuracy. The VGG16 architecture was originally proposed by Andrej Karpathy in 2015, and is based on the work of Geoffrey Hinton's ResNet50 architecture. The VGG16 model consists of three layers: a fully connected layer with 32 filters followed by two convolutional layers that have 64 filters each. In addition to

being fast, it also learns well from small amounts of data. VGG16 is a convolutional neural network that can be used for image classification. It was trained on the ImageNet dataset, and it has been shown to perform well in various tasks such as image retrieval and object detection.

The VGG16 architecture consists of a fully connected layer followed by two convolutional layers with stride 2 (i.e., one-dimensional). The output of the first convolutional layer is fed into the second convolutional layer, which also has stride 2. The output of this second convolutional layer feeds into another fully connected layer with stride 2, which is followed by a max pooling layer and dropout.

Fig 3.2 The basic architecture of VGG16



ResNet-50: Resnet is a neural network architecture that has been used to train the ResNet50 model. It was designed by Google and published in 2015. The paper can be found here: https://arxiv.org/abs/1512.05873 What are the main differences between ResNet and VGG? ResNet is more flexible than VGG, because it allows for fine-tuning of parameters through hyperparameter optimization (e.g., dropout rate). We will use this flexibility to optimize our network architecture for maximum accuracy on CIFAR-10, while still maintaining good performance on ImageNet dataset. Resnet is a neural network architecture that has been used in various applications. The original ResNet model was trained on ImageNet dataset, and the resnet-50 model was trained on CIFAR-10 dataset. It was later extended to include more layers, including convolutional layers. Why do we need it? The main purpose of using ResNet is to improve the performance of deep learning models. ResNets are very effective at improving accuracy and speed up training time when compared with other architectures such as VGG or AlexNet. They also have better stability than VGG or AlexNet networks during testing.

ResNet-50 with attention based deep learning: Attention based deep learning is a type of machine learning algorithm that uses attention to learn. The algorithm looks at the data in an unsupervised way and tries to figure out what features are important for predicting the outcome. This process can be seen as supervised learning with a few extra steps, which makes it different from other types of machine learning algorithms. The main idea behind attention-based deep learning is to use the input data as well as all its surrounding information (context). In this way, we can find patterns in data that might have been missed before because they were not present or too small to notice.

MobileNet with Web implementation: MobileNet is a deep learning framework that can be used for mobile app development. It provides the necessary tools and libraries to implement deep learning models on Android, iOS and JavaScript platforms. The framework has been developed by MobileNet team at Google Brain Team in collaboration with Qualcomm Research.

The main idea of MobileNet is to create an efficient way to train neural networks without using GPUs or other expensive hardware accelerators. This approach allows developers to use their existing devices without having access to high-end processors or graphics cards, which makes it possible for them to build apps that run-on low-end devices.

By using MobileNet we made a simple website where physicians or staffs can upload their images and get skin cancer diagnostic very quickly since it’s a light weight neural network it can directly be loaded on the local mobile or computer browser and will be much safer also.

All of the above work is carried out on Jupyter notebooks hosted by google colab. Our work can be found on our GitHub repository here: https://github.com/grvkr777/Major_Project

4. Members & Contributions/Tasks/Roles

18111006 (Alan Biju): Data Cleaning (verifying data and removing redundant data). Used scikit-learn, youtube tutorials, online articles as reference to do it. Performed Exploratory data analysis to gain insights from the dataset

18111015 (Ayush Rai): Mock data training on different dataset, used simple convolutional neural network from scratch to implement it. Splitting dataset into training and test sets, used scikit-learn (a python library) to do it.

18111016 (Banoth Naveen Kumar): Splitting dataset into training and test sets in collaboration with Ayush Rai. And provided deep learning articles and tutorials links.

18111025 (Gaurav Kar): Data Training and Coding. Used Jupyter notebook (a python opensource web application) and following python libraries Scikit-learn, Tensorflow, Numpy, Pandas, Seaborn, Matplotlib to implement it.

All of the team members contributed equally to design the website that we build using our deep learning model MobileNet.

5. Results

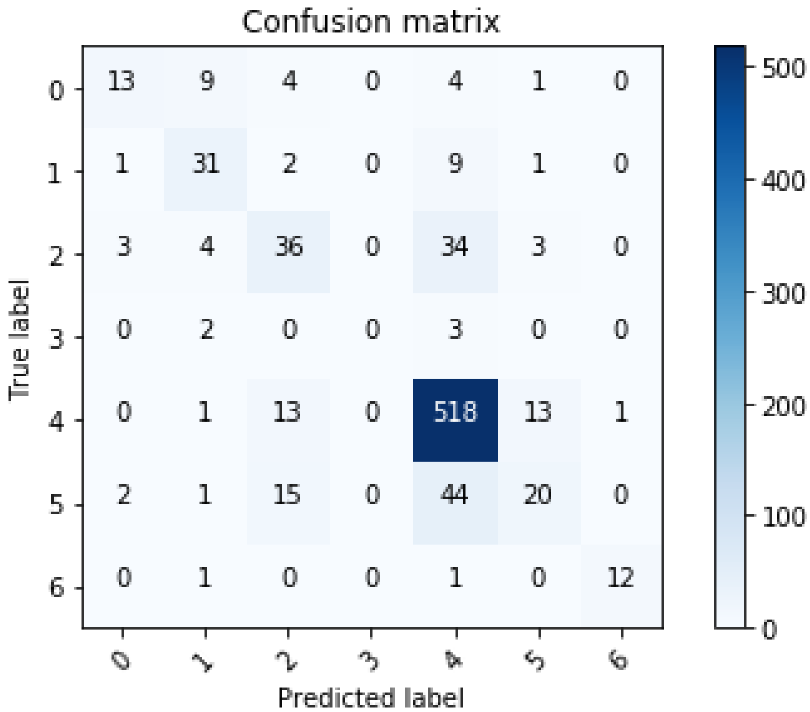
5.1 Convolutional Neural Network (CNN): Accuracy and other evaluation metrics are given below.

Fig 5.1: Accuracy of CNN

```
loss, accuracy = model.evaluate(x_test, y_test, verbose=1)
loss_v, accuracy_v = model.evaluate(x_validate, y_validate, verbose=1)
print("Validation: accuracy = %f  ;  loss_v = %f" % (accuracy_v, loss_v))
print("Test: accuracy = %f  ;  loss = %f" % (accuracy, loss))
model.save("model.h5")
```

```
2003/2003 [==============================] - 1s 694us/step
802/802 [==============================] - 0s 527us/step
Validation: accuracy = 0.785536  ;  loss_v = 0.586728
Test: accuracy = 0.764853  ;  loss = 0.616134
```

Fig 5.2: Confusion Matrix of CNN

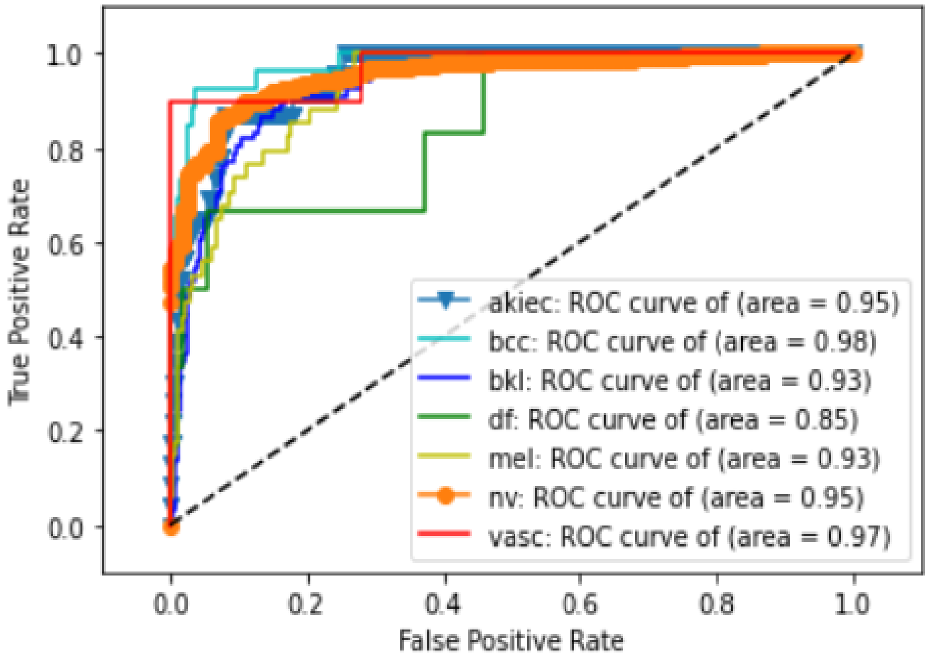


5.2 VGG16: Accuracy and other evaluation metrics are given below.

Classification Report:

	precision	recall	f1-score	support
akiec	0.62	0.22	0.32	23
bcc	0.54	0.77	0.63	26
bkl	0.57	0.48	0.52	66
df	0.25	0.17	0.20	6
mel	0.50	0.47	0.48	34
nv	0.93	0.96	0.95	663
vasc	1.00	0.90	0.95	10
accuracy			0.87	828
macro avg	0.63	0.57	0.58	828
weighted avg	0.86	0.87	0.86	828

Fig 5.3: ROC curve of VGG16

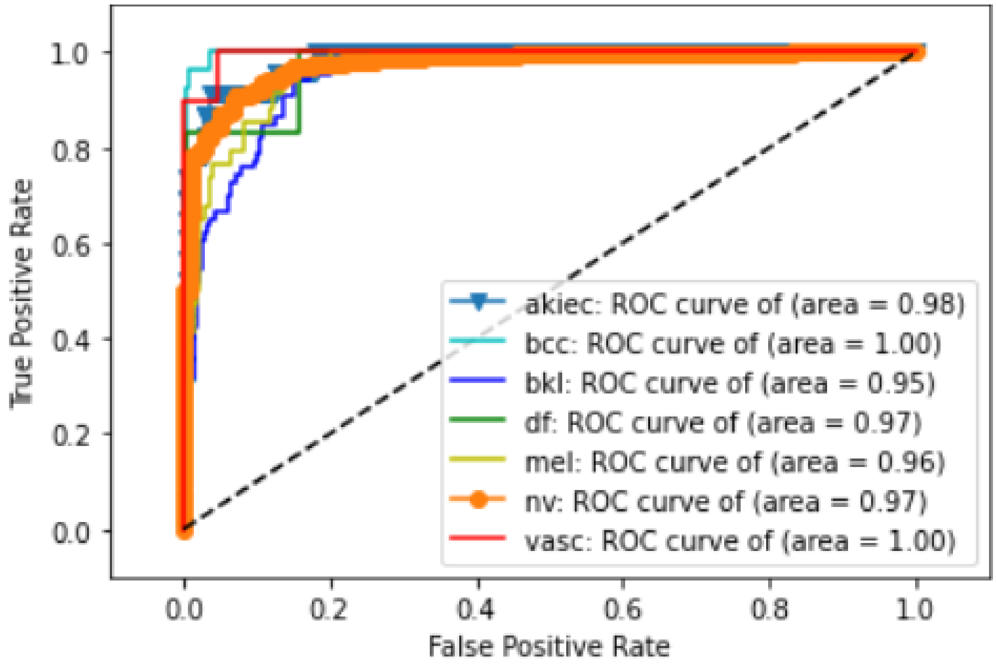


5.3 ResNet-50: Accuracy and other evaluation metrics are given below.

Classification Report:

	precision	recall	f1-score	support
akiec	0.74	0.74	0.74	23
bcc	0.91	0.77	0.83	26
bkl	0.67	0.50	0.57	66
df	0.80	0.67	0.73	6
mel	0.52	0.50	0.51	34
nv	0.95	0.98	0.96	663
vasc	0.90	0.90	0.90	10
accuracy			0.90	828
macro avg	0.78	0.72	0.75	828
weighted avg	0.90	0.90	0.90	828

Fig 5.4: ROC curve of Res-Net-50

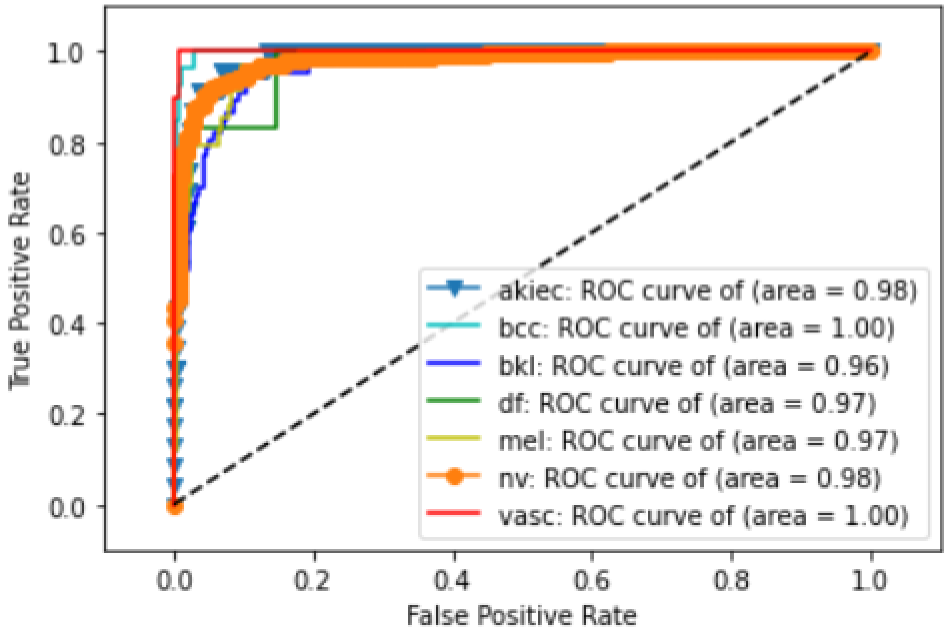


5.4 Attention based Resnet-50: Accuracy and other evaluation metrics are given below.

Classification Report:

	precision	recall	f1-score	support
akiec	0.67	0.43	0.53	23
bcc	0.88	0.85	0.86	26
bkl	0.67	0.70	0.68	66
df	1.00	0.50	0.67	6
mel	0.73	0.47	0.57	34
nv	0.95	0.98	0.97	663
vasc	1.00	0.90	0.95	10
accuracy			0.92	828
macro avg	0.84	0.69	0.75	828
weighted avg	0.91	0.92	0.91	828

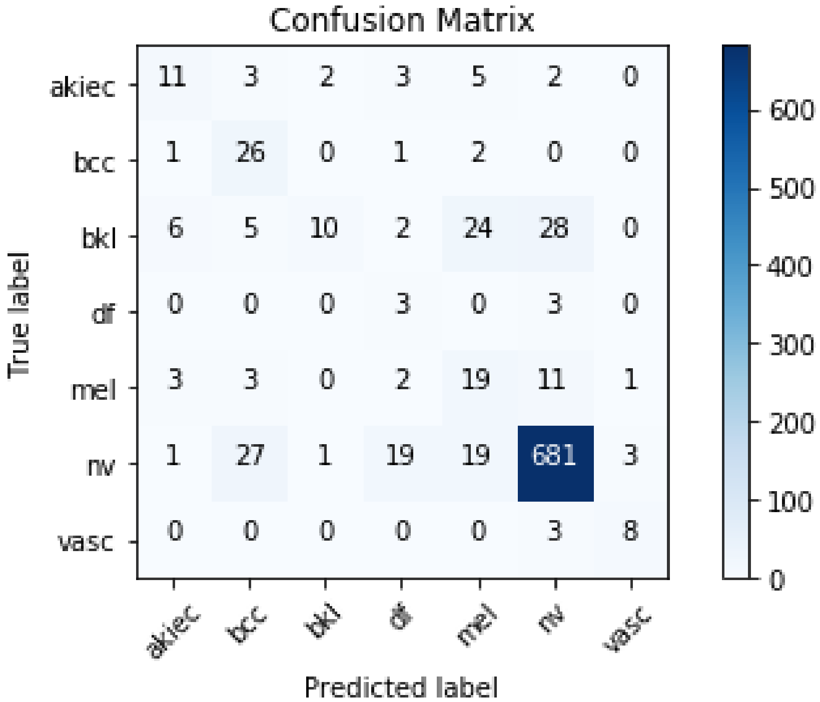
Fig 5.5: ROC curve of AB-ResNet-50



5.5 MobileNet with web implementation: Accuracy and other evaluation metrics are given below.

Accuracy: 82, Precision: 86, Recall: 81

Fig 5.6: Confusion matrix of MobileNet



The above model is a lightweight framework which we used to implement our skin lesion detection website.

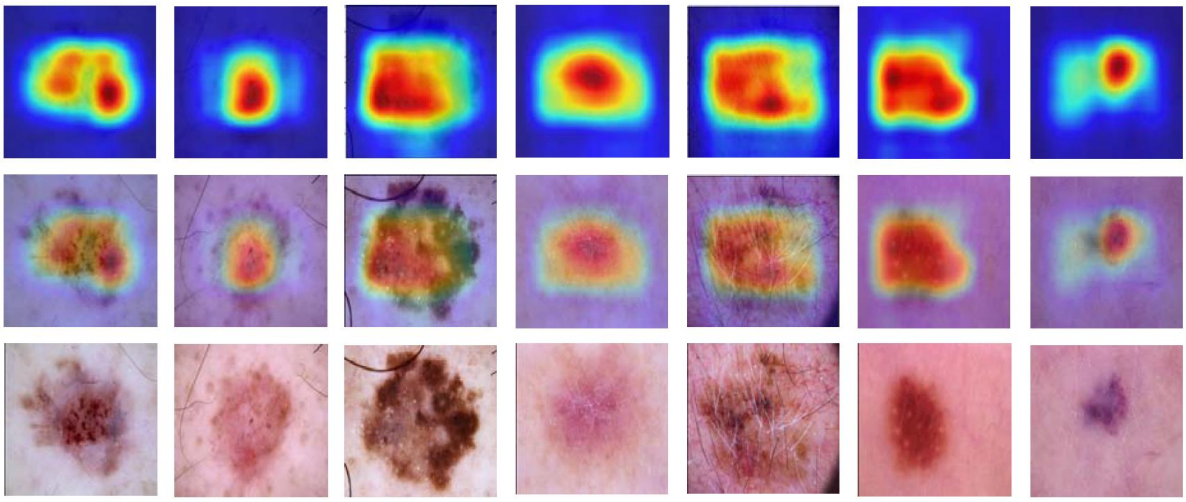
Link of the implementation of below mentioned web page which is hosted on GitHub: https://github.com/grvkr777/grvkr777.github.io

Link of the website: https://grvkr777.github.io/

Fig 5.7: Real time implementation of website screenshot

The above picture is a screenshot of our website which shows top three closest matched skin lesion sample. The model consistently gives top three closest matched prediction with an overall accuracy of 82 percent. The model is lightweight and scalable, it can accept multiple images and provide the result in real time.

Fig 5.8: Heatmap of our best performing deep learning algorithm: Attention based ResNet-50



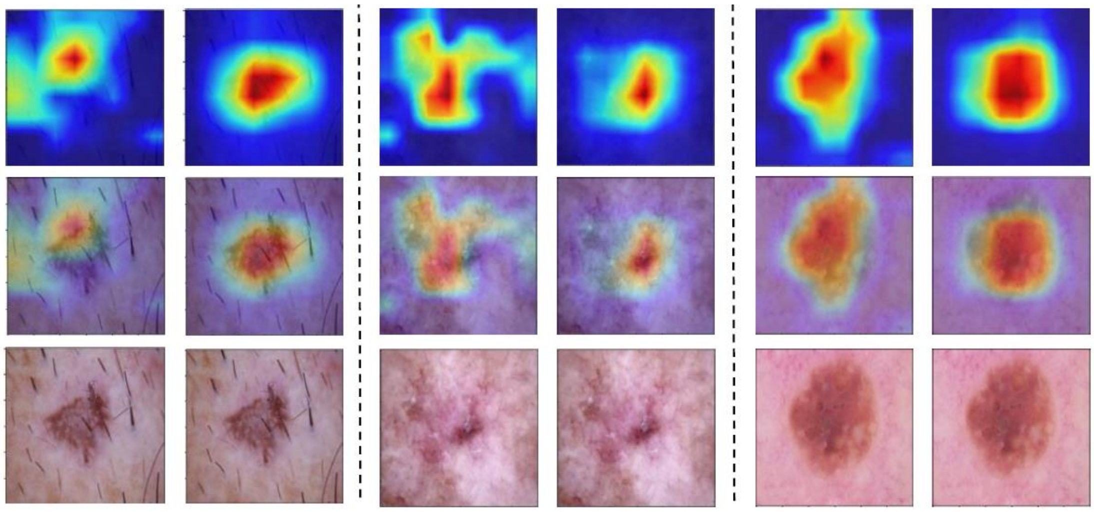
It can be seen from the above heatmap that the algorithm consistently detects correct region of interest by ignoring hair and non-infected part of the skin.

Table 5.1: Summary of all Deep learning algorithms

ML Models	Precision	Recall	Accuracy
CNN	75.14	76.33	77.03
VGG16	86.21	86.95	86.95
ResNet-50	89.81	90.45	90.45
AB-ResNet-50	**91.06**	**91.15**	**91.15**
MobileNet	86	81	82

Our aim at the start of the project was to apply state of the art deep learning algorithms and apply attention based deep learning technique to the best performed algorithm. We implemented different algorithms such as CNN, VGG16, ResNet-50 & MobileNet. After getting the best performing algorithm we applied attention based deep learning to it. We can see from the above table that our attention-based function worked as expected. It can be seen from the above table that the best performing model is AB-ResNet-50 which has the highest precision, recall and accuracy respectively.

Fig 5.9: Heatmap comparison of our best performing algorithm AB-ResNet-50 (right) with our first CNN model (left)



We can clearly see that the heat map of AB-ResNet-50 is far better and clearly defined, since it's the better algorithm with better precision, recall and accuracy respectively. AB-ResNet-50 is the best performing algorithm because it's implemented on top of ResNet-50 which was the previous best model, we implemented an attention based function in ResNet-50 to make it more accurate, in attention based deep learning unrelated regions which are not contributing to the detection process gets ignored since the weights are multiplied together to get almost zero, basically the unrelated regions gets ignored or the weights of that regions gets vanished and become very close to zero, this helps the algorithm to further improve the image detection process and in turn also improves the accuracy of the model.

6. Conclusion

In this project we implemented different deep learning algorithms to detect the type of skin lesions. We started with simple basic convolutional neural network which gave satisfactory accuracy of 76.48% accuracy, then we used VGG16 which gave us 81.16% accuracy. Our initial aim was to implement attention based deep learning on our best performing model to further improve our accuracy, our best performing model was Resnet-50 which had 90.45%

accuracy and after applying attention based deep learning the accuracy increased to 91.54%. Finally, we used lightweight CNN MobileNet to implement the skin lesion detection on a fully locally working website, it consistently returned the correct top 3 skin lesions. What we found after reading several deep learning research papers on skin lesion classification is that real time or real life use of deep learning models are very rare, researchers generally implement a deep learning model and focus on accuracy rather than real world use, so we tried to make a real world use case of our deep learning model developing a simple website which consistently give top three predictions of skin lesions. Although our website is a prototype and a lot of work can still be done on it, but the real time application opens a wide range of application of deep learning models which can further be explored. Our aim was to apply attention based deep learning on our best performing model and we succeeded in that regard, but something was missing so we tried to implement real time deep learning model so that it has some real world applications, we tried to demonstrate that physicians or staff can use deep learning based websites and can easily get consistent correct detection of skin lesions, we also allowed multiple selection of images so that images can be uploaded in bulk and can be classified in real time.

7. References

1. Nugroho, A. A., Slamet, I., & Sugiyanto. (2019, December). Skins cancer identification system of HAMl0000 skin cancer dataset using convolutional neural network. In AIP Conference Proceedings (Vol. 2202, No. 1, p. 020039). AIP Publishing LLC.
2. Faes, L., Wagner, S. K., Fu, D. J., Liu, X., Korot, E., Ledsam, J. R., ... & Keane, P. A. (2019). Automated deep learning design for medical image classification by health-care professionals with no coding experience: a feasibility study. The Lancet Digital Health, 1(5), e232-e242.
3. Sae-Lim, W., Wettayaprasit, W., & Aiyarak, P. (2019, July). Convolutional neural networks using MobileNet for skin lesion classification. In 2019 16th international joint conference on computer science and software engineering (JCSSE) (pp. 242-247). IEEE.
4. Sae-Lim, W., Wettayaprasit, W., & Aiyarak, P. (2019, July). Convolutional neural networks using MobileNet for skin lesion classification. In 2019 16th international joint conference on computer science and software engineering (JCSSE) (pp. 242-247). IEEE.
5. Huang, H. W., Hsu, B. W. Y., Lee, C. H., & Tseng, V. S. (2021). Development of a light-weight deep learning model for cloud applications and remote diagnosis of skin cancers. The Journal of Dermatology, 48(3), 310-316.
6. Çevik, E., & Zengin, K. (2019). Classification of skin lesions in dermatoscopic images with deep convolution network. Avrupa Bilim ve Teknoloji Dergisi, 309-318.
7. Carcagnì, P., Leo, M., Cuna, A., Mazzeo, P. L., Spagnolo, P., Celeste, G., & Distante, C. (2019, September). Classification of skin lesions by combining multilevel learnings in a DenseNet architecture. In International conference on image analysis and processing (pp. 335-344). springer, Cham.
8. Moldovan, D. (2019, November). Transfer learning-based method for two-step skin cancer images classification. In 2019 E-Health and Bioengineering Conference (EHB) (pp. 1-4). IEEE.
9. Jain, S., & Pise, N. (2015). Computer aided melanoma skin cancer detection using image processing. Procedia Computer Science, 48, 735-740.
10. Zhang, N., Cai, Y. X., Wang, Y. Y., Tian, Y. T., Wang, X. L., & Badami, B. (2020). Skin cancer diagnosis based on optimized convolutional neural network. Artificial intelligence in medicine, 102, 101756.
11. Hasan, M., Barman, S. D., Islam, S., & Reza, A. W. (2019, April). Skin cancer detection using convolutional neural network. In Proceedings of the 2019 5th international conference on computing and artificial intelligence (pp. 254-258).