

An Efficient Deep Learning Approach To Detect Skin Cancer Using Image Data

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A thesis submitted to the Department of Computer Science and Engineering
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Declaration

It is hereby declared that

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2. The thesis does not contain material previously published or written by a third party, except where this is appropriately cited through full and accurate referencing.
3. The thesis does not contain material which has been accepted, or submitted, for any other degree or diploma at a university or other institution.
4. We have acknowledged all main sources of help.

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Abstract

We propose and demonstrate an efficient deep learning approach to classify skin cancer using image data. The proposed approach is composed of several stages which are data acquisition, preprocessing and classification. For classifying skin cancer using image data and deep learning, four different convolutional neural network architectures, EfficientNetV2B3, EfficientNetV2s, InceptionNetV3 and DenseNet121 were used on this work. The CNN models achieved accuracies of 83%, 86%, 84% and 88% respectively on a testing split of the HAM10000 dataset. Moreover, each of the CNN models were ensembled in two different ways, one is where all the predictions from the four models were averaged and the other one is based on K-Nearest Neighbors approach where features from each of the CNN models were combined to fit a KNN model. The ensemble through averaging predictions achieved an accuracy of 90% and the ensemble based on K-Nearest Neighbors achieved an accuracy of 92%. Moreover, we demonstrated each of the CNN models using Explainable AI.

Keywords: Classification, Detection Deep Learning, Accuracy, Neural Network, Acquisition.

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Nomenclature

The next list describes several symbols & abbreviation that will be later used within the body of the document

AI Artificial Intelligence

CNN Convolutional Neural Network

HAM10000 Human Against Machine With 10000 Training Images

KNN K-Nearest Neighbor

ML Machine Learning

NAS Network-Attached Storage

ReLu Rectified Linear Unit

Chapter 1

Introduction

1.1 Background of Skin Cancer

The uncontrolled expansion of skin cells on sun-exposed skin is known as skin cancer. When skin cells grow and replicate in an unregulated, disorderly manner, skin cancer develops. Mainly, upper layer and lower layer which are known as epidermis layer and dermis layer are the two main layer in human body. Skin cancer initiates from the epidermis or the upper layer as the UV radiant directly hits in the upper part of the skin and the main reason of skin cancer is ultra violet light which comes from sun. There are three main different forms of skin cancer. First of all, Basal cell carcinoma is the most prominent type of skin cancer that arises from the basal cell of the skin. It mainly affects men more than women. Research founds that, every year more than 4 million of citizen in United States are being affected by Basal cell carcinoma. The sun's UV radiations are one of the key causes for this type of cancer. Face, neck, hands are the example of sun-exposed parts of human body and basal cell carcinoma generally developed on those body parts. The second leading form of skin cancer is called Squamous cell carcinoma and it is develops from the Squamous layer of our skin. Another name of this cancer is cutaneous squamous cell carcinoma or CSCC. Almost 20 percent people being affected by this type of cancer per year and at present the risk of this cancer has been increased more than 200 percent over the past 30 years. Finally, Melanoma is third types of skin cancer. The chance of being affected by this type of cancer is 1 percent but the case of mostly dead is accounted from this type of cancer. Unlike the Basal cell carcinoma, Melanoma mainly attracts women more than men who are below 30 years old. Day by day it's becoming the deadliest types of skin cancer because it helps of affect other body part very quickly when someone being affected by the Melanoma cancer. If anyone becomes affected by Melanoma and if it spreads to the lymph nodes then s/he has the chance of 99 percent to survive next 5 years. People who have less melanin on their skin are mostly in the danger zone for the skin cancer. Because melanin is such a component of our skin which helps to prevent the skin from the damage of UV ray. Moreover, Family background is also responsible for the Skin cancer. If anyone of your family had the skin cancer than there is a high chance that you might get affected by this. Furthermore, nowadays, we use different types of body lotion on our skin without checking the ingredients which causes cancer as well at the end. Skin cancer has 0 to IV stage. Most of the people take skin cancer very normally. But it is wondering that skin cancer can take off your life as well. Of

course, it is very easy to prevent if it can be caught at the very early stage. When a patient is in 0 or 1st level of cancer, only biopsy is enough to get rid of. But when a person is in the 3rd or 4th stage of cancer, there are some other types of treatment such as surgery, chemotherapy, radiation. Chemotherapy is mainly for the 4th stage of patient which helps to kill the cancer cells. After chemotherapy, one needs to take radio therapy so that again the cancer cell cannot develop in the same place or cannot be divided to the other part of the skin. But if it is too late to find out it, then death is the final result. Though skin cancer is one of the risky cancers but also preventable nowadays. Before going outside from the home, one must need to use sunscreen properly. Even some people think that sunscreen is required only in the summer season which is a wrong concept. Sun scatters harmful UV lights all over the year so we must need to use sunscreen in a daily basis. As much as we can, we should avoid the UV rays of the sun in the middle of the day and also, we can use protective clothes so that sun can not directly hit on our skin. These types of steps can protect us from being affected by skin cancer. Most of the People are not that much conscious regarding their skin. Though some moles are there in our skin by born and most of the moles develop in our skin up-to the age of 40. Whenever someone sees any kind of changes in their skin such as itching, color change, bleed without further delay, they should consult a doctor. We should keep in mind that skin cancer is preventable if the disease can be found out in the first stage. So, everyone should be careful and follow the rules to prevent themselves from being affected by the skin cancer.

1.2 Problem Statement

The ultraviolet rays coming from the sunlight damages our DNA, which is the main reason of being affected by skin cancer. The first sign of a non-melanoma skin cancer may be an unusual skin growth or sore that doesn't go away. On the skin's surface, skin cancer may first show up as a nodule, rash, or a strange patch. These lesions could be raised and easily ooze or bleed. The size or shape of the visible skin mass may change as the cancer spreads, and it may also invade deeper skin layers. If you notice any suspicious or changing marks on your skin, see a dermatologist right away because it may be challenging to tell one type of skin cancer from another. Skin cancer is such a type of disease which we don't even notice and because of this negligence we have to pay a heavy price. Thousands of people in first world countries are dying because of skin cancer where advanced medical support is just a door away. The count will be far higher if we consider the situation of the poor countries such as Bangladesh. Here, people don't have the basic idea and compare skin cancer with normal skin rashes and another reason is because of the ongoing environmental pollution, this affects our skin badly and eventually our skin is attacked by different variants of skin lesions. A very dangerous type of skin cancer is melanoma. Only 2 It causes the most death among all the skin cancers. In 2006, 3.5 Million skin cancer patients were recorded in the USA. Among them 80 percent was Basal cell carcinoma. Around 7990 people died because of melanoma last year in the USA and among them almost 65 percent of the victims are men. Melanocytic nevus often makes the victim feel stressed or anxiety. In the last stage melanocytic nevus hits our spinal cord and damages our brain. While dermatofibromas can affect anyone at any age, they are most common in people in their 20s to 40s. Vascular lesion is

another dangerous form of skin cancer. Vascular lesions can be divided into three main groups: hemangiomas, vascular malformations, and pyrogenic granulomas. Even though these birthmarks occasionally have a similar appearance, their causes and required treatments vary. According to the reports of WHO in 2020, Around 853 people have died in that year in Bangladesh due to skin cancer. We can say that the actual number is way bigger than the recorded number as most of the people live in the rural area in Bangladesh, who don't have the basic medical support. If a person is detected with skin cancer in our country, then what's the cost of the treatment ? Around 7 lakh taka. That's a huge amount which is undoubtedly unbearable for most of the people. Main problem among us is that we don't take skin lesions seriously. And besides that the government has never given importance to this to make the people aware. As most of the people are still illiterate to gather enough knowledge about this . Where latest technologies like ABVS, Agility Synergy, Brachytherapy are used to detect skin cancer in developed countries. Some other famous processes of curing skin lesions are Freezing, Chemotherapy, Radiation therapy, Curettage and electrodesiccation or cryotherapy. But the only way of detecting skin cancer in Bangladesh is skin biopsy. It is mainly used to remove the spot from the skin and after that, skin cancer can be identified. There is no way to identify the skin cancer without this process, which is a big problem for the human being. Since, biopsy requires excessive bleeding and it is a bit painful process. Sometimes, infection occurs in the skin too. So, when it comes about biopsy, people usually do not want to do this and skin cancer increases. Again, there is no way to feel the skin cancer so, people cannot understand whether s/he is being affected by skin cancer or not in the primary stage. Most of the time, there are some major symptoms such as burning the skin, itching etc. However, the skin cancer grows very slowly that is why people cannot easily feel the symptoms. As As a result, when they finally come to visit the doctor, it becomes too late for them. Moreover, it takes 2 to 3 weeks to get the result of the biopsy. That means, it requires almost 14 to 21 working days to get the report which is usually a bit late and within that time, cancer may increase in the basal cell if they continuously go under the sun or do not maintain the rules regulation to be safe from skin cancer.

1.3 Aims and Objectives

The aim is to detect skin cancer by following the best approach which ensures the efficiency of the CNN models . Through the multi class classification from the proposed dataset HAM 10000 we aim to find the disease with the fewer parameter models and less computational cost which will make it more relevant in detecting the disease with best accuracy and less cost. By implementing our ideas with the help of existing pre-trained models we want to break all the previous accuracy related to skin cancer classification. We want to make our models more efficient and accurate in order to detect this disease in very short period of time so that the bad effect and more danger in the community can get reduced. Our main objectives are given below :

- Firstly, we want our models to detect more accurately then the previous models used.

- Secondly, we want our models to detect the disease more efficiently.
- Thirdly, we want our the computational cost of our models to get decreased.
- We want that our model to be global so that it can be accesible .
- The models that we are proposing can be very easily used with less amount of cost involved as a result this can be used by the people who do not have much access to the advance medical facility.
- The models that we are using can be use for advance usability in the medical sector when we will be reaching our goals of making such models .

As we all know that skin cancer is getting increasing day by day it is very crutial for all the doctors and engineers to collaborate together in order to solve those problems .Saying that , the machine learning models comes to the light in order to tackling many real world problems .Now a days the medical sector is very much dependent on technologies. Any kind of the disease detection is now done by the help of technologies. In most cases it is seen that the cost is very high in order for the detection of the disease. So, researchers are always trying to make technologies more cost friendly so that it can be available to every part of the world population. The affordability of the cost are targeting to get reduced by using more efficient and accurate models in order to minimize the computational cost .So we are also planning to build certain models which will be helping us to get fullfill our target. By taking the models with the less amount of the parameters and certainly with the high top-1 accuracy we can be used so the computational cost get reduced and the model that we are proposing can give the best computational accuracy with less cost however having higher accuracy .The aims and objective of making such models comes from the necessity of the people around the globe and because of increasing amount of growing such disease .

Chapter 2

Literature Review

In the research paper, [4] it states that, there are mainly three types of skin cancer. Basal cell carcinoma, Squamous cell carcinoma, and Melanoma are illustrations. Even though Basal cell carcinoma is the most dangerous types of skin cancer however, non-Melanoma skin cancer is another type of cancer which is the most frequent malignancy in German country. This mainly affects the fair skin. That is why,

people who live in German or United States, they are fair-toned people by birth and affected by this non-Melanoma skin cancer more. According to the gender, it mainly works for 47 and 34 cancer but men who are older get affected more. According to the report of WHO in 2003, 2-3 million per year in German and 3.5 million per

year in United States are being affected. Following the report in Schleswig Holstein in recent year (2008-2010) by age, gender, histology, 7,302 women and 7,688 men are getting this cancer. The incidence rate for this type of cancer is very frequent and most of the cases, people who are more than 40, they are the victim for this cancer. NMSC mainly contains two main types of skin cancer: BCC SCC. Basal cell carcinoma mainly grows from sun exposure and Squamous cell carcinoma grows from UV ray. This article mainly covers the up-to-date information about non-Melanoma skin cancer in Germany. It talks about the BCC SCC and the impact of the cancer. It also talks about who are the main victim for this cancer and also the group of people, the skin color, age and different ethnic group of people who are the attraction for the cancer. In Paper, Skin cancer is nowadays one of the most leading cancers among all other cancers in the world. United States is more conscious about this part and that is why every year they work on it by collecting datasets from their country. Mainly, National Cancer Institute's (NIC's) collects the information's from the whole country. They have powerful software where the native Americans do registration and test their skin primarily. In 2021, 1,898,160 new cancer cases are projected in the America. But the problems after Covid-19 is people are not taking care of this part at all. If we talk about the race and ethnicity, skin cancer may vary on these. Such as, race is here an important part because, people with fair skin are affected by skin cancer more. The reason behind this is- fair skin has less amount of melanin. So, the sun directly hit on their skin and the skin cell can easily be damaged and increase cancer. In America, breast cancer and lung cancer are very common and death rate is high as well. In the same way, in recent years, skin cancer is also increasing very frequently. Statistics shows that, people

who are below 40, they are becoming affected by skin cancer more. The reason could be family background or they go outside in the middle of the day more. Though since 1991, the result of death rate decline but the progress is a bit slower. Proper treatment can reduce the death rate for the skin cancer will be more helpful. In the research paper authors [14] focused on that skin cancer is one of the most common and frequent type of cancer nowadays. The number of the patient for skin cancer is increasing day by day. Skin cancer is three types. Among them, Basal cancer is most risky and 20upper skin of human body. On the other hand, SCC is the second type of skin cancer which mostly affects the inner skin and only 1Another type of cancer is called Melanoma cancer. People who are fair skinned they mainly affected by this cancer. So, mostly the people from German, United states are in the danger zone for this one. Skin cancer is very difficult to feel. Dermatologist cannot detect it from simple Dermoscopy image. Most of the cases, biopsy is the only case to detect the skin cancer and pathology examination is another way to find out or detect the skin cancer. Biopsy is the most painful and sometimes risky process for the patient. Again, people are nowadays more conscious about COVID-19. So, they do not think more about their skin or cannot feel anything as skin cancer do not show downs any symptoms in the primary stage. It indicates that detecting the skin cancer is very difficult anddermatologist face different problems to detect it. That is why, in 2018, Tschandlet, al., published a research paper where, the published 1000 Dermoscopy image from Australia. They tried to identify whether it is possible to detect the cancer from image lesion or not. Around 8000 of the images required pathology. Nowadays, there are different types of software in the world and in 2017, researchers from Stanford University were able to conduct a study to identify the skin cancer by neural network model. In the same way, data sets are used to invent new software's to detect skin cancer easily. Skin cancer[11] is the out-of-control growth of abnormal cells in the epidermis, the outermost skin layer, caused by unrepaired DNA damage that triggers mutations. Epidermis is the outer layer of the two main layers of the skin. A part of epidermis which looks different from surrounding area is called skin lesion. There are so many methods to classify skin lesion but convolutional neural network is more superior over other methods. In the research authors propose a fully automatic computerized method for skin lesion classification which employs optimizing deep features from a number of well-established CNNs and from different abstraction levels. Malignant melanoma is one of the deadliest types of skin cancer which is responsible for 10,000 deaths annually just in USA. To detect better image quality of skin cancer dermoscopy device is used. In the research it's been hypothesis that using pertained models, extracting features from different layers and ensemble learning which can lead to classification performance competitive specialized state of the art algorithm.. Moreover, three different models are utilized which are Alex Net, VGG16, ResNet-18 which are pertained on ImageNet. In this research 4 types of materials are used which are Dataset, Preprocessing, deep learning models and classification and Fusion. In the dataset they use training, validation and test image of ISIC 2016 competition for training the classifier. They use 2037 color dermoscopy skin images which includes 411 malignant melanomas. The images are of various sizes from 1022x767 to 6748x4499 pixels and the number of images is 150 set. In preprocessing they use three steps. First, they normalize the images by subtracting the mean RGB value of the ImageNet dataset. Next images are being resized. After that they augmented the training set by rotating images in different angle. In deep

learning model they use the shallowest variations of VGGNet and ResNet to prevent over fitting. They use first and second fully connected layers and concept detector layer. In classification and fusion above labels are then used to train multi-class linear support vector machine. They train different classifier average the class scores, to obtain final result. To evaluate the classification result they map SVM scores to probabilities. To get the final result they evaluate 150 images provided by ISIC. For evaluation, they employ the suggested performance measure of area under the receiver operating characteristic curve. In conclusion, there are some limitations like number of pertained networks are limited but extending the model to incorporate, training dataset to lead better result, resizing images to very small patches could be the potential solution for the problem. In conclusion researchers have demonstrated that pertained deep learning models can be exploits. Though good classification results demonstrated on the challenging images but in future fusing deeper feature can lead to better predicted models. One of the deadliest and dangerous type of cancer is Malignant Melanoma. Another one is nonmalignant melanoma. In this research author [13] Vijayalaskshmi proposed that Melanoma can be cured if it's identified in early stage but if it's identified in last stage, it can't be cured as it already spread deeper into the skin. Melanoma is caused by Melanocytes and exposure of skin to UV radiation. The author designed a model which has 3 phrases which are collection of data, segmentation and feature extraction designing and training the model. Methodology usually use four components- Collection of data set, hair removal, shading removal, glare removal. To design the model the author used three different methods- Neural network, support vector machine, convolutional neural networks. In neural networks back propagation algorithm is used. Back propagation is used for training the multilayer perceptions. While designing the neural networks some problems are being faced. To minimize the problem some steps are taken like calculating the error, minimizing the error, updating parameters, prediction made by modalism (support vector machine) is an algorithm which is used to classify data into different classes. SVM have some features like it trains on a set of labeled data, it can be used for both classification and regression problem. Also, SVM can be used for classifying non- linear data by using kernel trick. The back propagation algorithm looks for the minimum value of the error function in weight space using a technique is called delta rule or gradient descent. Convolution Neural Network (CNN) is basically demonstrated to identify faces, objects and traffic signs better than humans. It's also used in self driving cars and robots. CNNs are trained using data labeled with the respective classes. CNNs basically learn the relationship between the input objects and the class labels and compromise two components. The hidden layer and the regular layer. In regular layer each layer is formed by a set of neurons and one neuron of the layer is connected to each neuron of the preceding layer. In conclusion the main goal of the project is to determine the accurate prediction of skin cancer and classify it into malignant and non-malignant melanoma. The positive side of the methodology is that it detects cancer very quickly and any data set can be used here to find the efficiency. In early century cancer is one of the deadliest public health issues. Melanoma is one of the most dangerous types of cancer because it spreads very rapidly. Dermoscopic image provides a significant aid. The author Md. Maruf Hossain and Emrana Kabir Hashi proposed that nowadays feature from an image can be easily extracted by a large convolutional neural network. In the dataset 33000 training images of 2056 individual patient are gathered. Among them just

1.76imbalanced. So previous year dataset is used. Latest dataset includes 25,332 photographs of skin lesions in JPEG format. The dataset provides metadata which contains information about patient. This dataset must be optimized until it can be loaded. To process the data triple stratified data are used to organize the dataset. Also, there are 434 duplicate images in the training result leak occurs when one picture is the generated training fold and duplicate is in the validation fold then leak occurs. To avoid leak 434 duplicate photographs were deleted. Mainly python is used for this language. In geometric augmentation when data is not sufficiently big, skin lesion scale is maintained. As a result, photographs are randomly cropped. Sample of skin lesion image is collected using different devices and lighting. The augmentation is done by using the tensor flow library. Fine tuning an image trained model for skin lesion means samples are running across the network and features are extracted from various layers. Four basic items are needed for deep learning model- 1) Large volume of data 2) large models 3) competitive model design and 4) training 8 Techniques. In first experiment they use 20000 images from training data and validation data set. The highest cross validation accuracy was 0.67. Then VGG-16 was applied on the same train. The weights of a VGG-16 model pertained on the Image dataset were used to initialize the retained layers. Ten flatten layer was added after that. To measure the effectiveness of a statistical or machine learning process assessment metrics may be used like deep learning frameworks or algorithms must be evaluated. Different model performs differently. So, to identify the most effective augmentation process all different augmentation was applied individually on EfficientNetB5. In conclusion, the research suggests using Data Augmentation and Deep learning to increase melanoma classification accuracy and investigate the impact of image augmentation on the classifier's efficiency. As skin cancer affects millions of people around the globe, this research may be used as a key testing project on various deep learning models in this study. Melanoma, on the other hand, can be curable if diagnosed and detected early enough.[10] As a result, an effective Computer Aided Diagnosis (CAD) system for melanoma identification and diagnosis is required. A new totally automated approach for detecting melanoma. Deep Convolutional Networks are paired with a SoftMax classifier and a dice loss function in this system. This model combines all segmentation, feature extraction, and classification operations in such a way that no additional computational resources are required. They're a convolutional encoder-decoder design with a lot of depth. Lesion classifier with a multi-stage and multi-scale technique. The Encoder-Decoder Network, which is used to train deep convolutional neural networks for categorization of skin lesions images, is depicted in the diagram. The network is trained using the training dermoscopic pictures as well as the ground truth labels (annotations). The images are then pixel-wise classified and the melanoma region of interest is identified using an extra module that combines the dice loss function with the SoftMax classifier. Deep learning, according to all of the researchers [22], is when a computer expressly grasps and evaluates tasks from images, text, or sound. It outperformed other approaches in terms of efficiency at higher levels, assisting customers in meeting user criteria. Deep learning is now being used in everything from automated driving to medical equipment. In the healthcare industry, treatment is projected to advance based on previous history and disease. Since most skin cancer patients will contact them before being sent to dermatologists, AI classifiers will continue to play an important role in supporting non-dermatologist clinicians. When it comes to analyzing skin

photos for cancer detection, data mining technology has just 89.5 percent accuracy. It is feasible to determine the cancer risk levels at an early stage using machine learning methods based on the score generated for each element according to their impacts on skin. The work demonstrates how to create models and use them to classify dermal cell pictures. With 2000 dermoscopic images, our model achieves a high level of skin lesion segmentation and melanoma detection accuracy. There are no defined evaluation test datasets for CNN classifiers to measure their efficacy. To determine categorization efficiency, it may be preferable to have tests conducted by a third-party agency. The major goal of this study is to predict the type of skin cancer in order to accelerate treatment at an early stage. The classifier is fitted with the extracted top characteristics from the convolutional layer to distinguish between 9 benign and malignant moles. The pixel values of images are classed as benign or malignant after they have been normalized by dividing all RGB values by 255. Spyder editor and Anaconda navigator are used to code the Python scripting language. Skin cancer disease is predicted using the ISCI Skin Cancer Dataset, which contains 1800 photos of benign moles and 1497 images of malignant categorized moles from individual patient records. Skin cancer is one of the most common cancers in the United States today, according to Dildar [18]. Melanoma is a type of skin cancer that is deadly, rare, and lethal. According to the American Cancer Society, melanoma skin cancer accounts for only 1 of all cases, yet it is connected with a higher death rate. It starts when normal melanocytes get uncontrollably large, resulting in a malignant tumor. The significance of early identification in the treatment of skin cancer cannot be emphasized. Thanks to computer-based technologies, skin cancer indications can now be diagnosed in a more comfortable, less expensive, and faster manner. Many deep learning methods have been investigated in recent years for computer-based skin cancer screening. Skin cancer remains deadly cancer affecting populations worldwide. Since the disease is fatal, early detection is critical towards improving the survival chance of patients. Admitting, a shortage of qualified experts and sophisticated medical equipment has affected the fight against skin cancer. In this paper [4] Aakriti Adhikari looked into the latest research efforts to advance skin cancer detection and classification through variants of DCNN architectures. Transfer learning, fine-tuning, ensemble approach, data generation, and augmentation are all effectively used for minimizing insufficiency of labeled data, which is prone to over fitting. It also contributes to improving the efficiency of skin lesion classification in CAD systems in general. Application areas such as medical imaging whereby large-scale training datasets are technically unavailable, building a rich data set covering skin lesion samples from 7 vast populations that includes extremely rare cases (out-of-distribution detection) is crucial to tackling the problem of scarcity of labeled data, which will also facilitate the advancement of skin cancer detection field further. Detecting [6] skin cancer in the early stage is a bit crucial part because if medical fails to detect the level of fatality of melanin, then the cancer may grow fast in the skin. Advanced dermatology field is continuously trying to find out different and easy processes to detect the skin cancer in the early phase. As a solution, they are now following data synthesis technique where, by using high quality body image with 1300 biopsy and 400 body images of back, leg, chest. In this process, they try to combined two images from it and then force the pixel to focus on the texture information. Furthermore, in this system at first, they detect the malignant and benign lesions and then blend them onto the image. When the system

gets informed about the lesion and the body image, the system then tries to convert the result in image form from the given data. In this way, this system forwards an input image by CNN and gives the output pixel wise. To experiment this process, medical team already test almost 108 clinical images. Again, they exhibit human interpretable detection and performance over baseline. They focus on the pairs and pixel wise corresponding from human body. When the network is concerned about the data, it gives the output. In this way, AI system is now making the medical sector more advanced and trying to find out the solution to detect the malignancy in the human body. Every year,[16] skin a certain number of people become affected by skin cancer worldwide and the number of death rate is also increasing nowadays. In USA, almost 5.4 million people are being affected. The reason behind this is skin cancer is not too easy to identify in the early stage. When people visit the dermatologist with their skin problems, they check their skin 10 with eyes and usually do not use any types of machines or tests. But skin cancer cannot be identified with naked eyes. It requires deep inside test from skin cell. However, when the data of the skins can be scanned by using technology, it can provide almost 100result. In this process, mainly the image of lesion or pigmented skin will be needed. By using deep learning studio (DLS), we can drag and drop the data in the process and can make a suitable model. There are two versions of DLS- desktop version and cloud version. But the main problem with this is, setting up parameters is a bit difficult since there are no particular rules for it. The filter size should be 3*3 and dropout percentage should be 0.25- 0.50 to boost up the training. After setting up this stage, DLS model provides neural network model. It includes some steps such as- preparing data, learning the data set, classification, check the result and so on. By this model driven architecture, the DLS model uses the cell images and train the data to detect the skin cancer. by this method, 99.77 percent accurate result can be identified. Melanoma [21] is a severe type of skin cancer that has spread dramatically in the last 30 years. The main reason behind increasing of mortality rate is- it is not easy to detect the skin cancer in early stage. That is why advanced medical field nowadays are using different types of deep learning techniques via dermatologic images to overcome the situation so that, people can get a reliable service by those tools. This method mainly works in two stages. In stage 1, by using Mask RCNN, it crops a bounding box around the skin. It is used to detect the candidates who carries skin lesion. Once Mask RCNN able to identify the probabilities of lesion in the skin, then they are transferred to the next stage. In stage 2, it classifies the bounded box by using ResNet152. Then they prepare the network to exhibit the database from ISIC 2017 which carries almost 1995 dermatoscopic images. In total, this convolutional network has approximately 60 million parameters that must be changed throughout the process. After experimenting several tests, it is found that this test does not fully guarantee a better result. The performance may vary by common transformation such as rotation, flipping etc. When it takes hug image, it cannot properly identify the skin. However, eVida M6 performs better than the discussed stages. It is a more trustable predictor since it contains balance between accuracy (0.904), sensitivity (0.820) and specify (0.925). So, the result indicates that it is required to improve the test results obtained in the state of the art to detect the malignant or benign in the skin. [10] In recent years, the use of machine learning and AI is increasing in each sector and the progression in the medical sector is also noticeable. Deep Machine learning technology is using to detect skin cancer

in western country. Medical researchers used faster R-CNN and RPN algorithms to detect skin cancer in the human body. Their main target skin was from brown to black. By using clinical image of human body, they tried to identify the classification of skin cancer from pigmented skin lesion. In this method, they first of all collect skin image, train the network of deep learning model, then they use test time augmentation. Finally, 10 board certified dermatologist and 10 trainers run the experiment. After getting the result, they compare their performance. They are trying to invent such a machine where, by using the mobile phone, people will be able to identify the skin cancer in their body. But it is difficult to identify the cancer from eczema. Since this test is implementing for the brown to black pigmented skin, so the researchers did not include this cancer in this test. Most of the time, people are not concerned about their skin disease at all. That is why they found out their skin cancer at the last stage. The main target of using this learning machine is so that they can detect their skin condition early and can start the treatment early as well. They are trying to make it easy so that all types of people can use this method by themselves. That is why they are inventing wearable devices for them. This method helps to identify the classification of skin cancer more accurately than the dermatologists. It is found that, this leaning not only able to identify the melanoma 11 skin cancer but also can detect the basal carcinoma too. Skin cancer[17] is one of the most hazardous types of cancer which is difficult to detect in the primary stage but extend to the other parts of the body within a very short time. That is why, in developed country the use of deep learning system is increasing. Data augmentation plays an important role to identify accurate result. It takes less time, save human life by accuracy as well. In this paper, 9 types of classification of skin cancer are identified by Convolutional Neural Network. These are actinic keratosis, basal cell carcinoma, benign keratosis, dermatofibroma, melanoma, nevus, seborrheic keratosis, squamous cell carcinoma and vascular lesions. To identify which types of cancer is increasing in someone's skin, image augmentation is used. By selection the image, network transfer data to the machine, after some phases, the data provides accurate result. Here, 79.45 percentages is shown by the CNN model. In 2015, an upgraded architectural learning method has been invented called "U-Net". Again in 2018, the more developed technology has been invented called R2U-Net where by using the images and proper analytical method, skin cancer can be detected properly. On the other hand, DL-based method is also very known method where ISIC 2016 and 2017 dataset are used. Furthermore, proposed CNN model contains five categories coevolutionary units. This is how the deep learning technologies are making the dermatologist more advanced in their working sector. Non-Melanoma skin cancer[1] rate is increasing dramatically day by day. Among the three types of NMSC, basal cell carcinoma is 80 percent, squamous cell carcinoma is 20 percent and others carry only 1 percent. In Germany, the skin cancer rate is impacting very badly. Here, treatment for this type of cancer is very costly. . In this SCREEN training program, researchers think that sun exposer is main element of skin cancer. when UV-ray badly hit the non-melanoma skin, cancer cell starts to raise inside the skin silently. Screening could improve NMSC treatment by allowing for earlier diagnosis, reducing recurrences and overall expenditures. However, if a significant fraction of the additional discovered lesions would not have been noticed during the patient's lifetime without screening, it cannot be ruled out that screening will raise morbidity and expenses. To solve this issue, screening on skin can save the life of a

human. Also, proper screening can help to improve the treatment of non-Melanoma skin cancer. Machine learning [19] methods for skin cancer diagnosis are rapidly being developed using publicly available skin imaging datasets. The combination of MEDLINE, Google dataset, network training all together helps to run the image dataset to detect the classification of skin cancer nowadays. On images acquired from demographics other than those on which the algorithms were trained, machine learning algorithms utilized for medical image classification have been found to underperform. On skin lesion photos of White patients from the United States, an image classifier algorithm trained and validated mostly on images of east Asian skin underperformed. There are 106 950 photos in 21 open access dermatology datasets for skin cancer, as well as 17 open access atlases that are freely accessible to researchers and the general public. Although this is a rich data resource for innovation, the clinical utility of these photos alone is limited due to a lack of openness in metadata reporting for clinically important factors such as ethnicity and Fitzpatrick skin type. These concerns have been reported in ophthalmology¹⁴ and radiology databases as well as dermatology. However, the disadvantages of AI are if someone run the wrong dataset or if they misdiagnosis the performance of algorithm them then it may cause serious level problems. To avoid such incident, it is necessary to develop imaging biomarkers, the network should be trained properly and also the image layer should be given by following the rules. innovation, the clinical utility of these photos alone is limited due to a lack of openness in metadata reporting for clinically important factors such as ethnicity and Fitzpatrick skin type. These concerns have been reported in ophthalmology¹⁴ and radiology databases as well as dermatology. However, the disadvantages of AI are if someone run the wrong dataset or if they misdiagnosis the performance of algorithm them then it may cause serious level problems. To avoid such incident, it is necessary to develop imaging biomarkers, the network should be trained properly and also the image layer should be given by following the rules. AI [15] is making medical sector more advanced nowadays. Artificial intelligence algorithms used for skin cancer diagnosis across various modalities of skin lesion datasets, which now makes comparison between AI algorithms and dermatologists/dermatopathologists. Before involving deep learning methods in medical diagnosis, it requires manual test but recently, it requires magnetic resonance imaging, computed tomography and so on. In the manual test system, scientists collect the hair of the patient, test the skin, eye etc. which takes a long time and most of the time, this does not provide accurate result. On the other hand, Esteva et al. already used 129,450 clinical dataset and then compared this result with 21 board-certified dermatologists. They collect the body image, train the network system to crop the image and find out the lesion in the skin. Following this process, they get the 83accurate result at the beginning. But, the main challenge with deep leaning method is if the image quality is not that high than the data set cannot work properly. Moreover, to get the exact output, network system has to be more trained and the balance in the data is also required. When they want to find out any new types of skin cancer, it does not provide any solution as the new data is not inputted there. AI system provides you the amount it is trained in the dataset. Moreover, if the data could be balanced, data augmentation could be enhanced and if the digital pathology for computer aided diagnosis can be enhanced properly, there is a huge opportunity in this sector for medical system. If these challenges can be solved and improved then this system will help to save human life and will make it

more effective as well. Skin cancer [20] is one of the very dangerous types of disease nowadays throughout the world. If it is not identified at the beginning, it will grow very fast and spread to the other part of the human body. Most of the time, skin cancer is tested manually which does not provide accurate result always and it is a bit expensive too. However, medical science is now more advanced and they are trying to implement the use of machine learning to detect skin cancer. that is why, CNN is proposed to use by which skin cancer can be identified. In this paper, scientist used CNN and VGG16 with 2742 images onto the ISIC dataset. When they changed the layer of images, the number of parameters increased almost 134 million. In this way, it provides 93 percent accurate result. Here, CNN is a very well-known network system. It recognizes the image from the dataset. ResNet50 is another system which is also used to identify the skin cancer. This system has been run in the Google Colab along with the python 3 Google computer. After that, the dataset become normalized in the SVM system. This is how at the end they classified the skin cancer type and predict the result with 83 percent accuracy. Scientist got 66 images of benign and 43 images of malignant. In the near future, more developed network system can be identified. Even though, in this given paper, they were able to identify two types of skin cancer but very soon the use of deep learning machine, we will be able to identify any types of skin cancer with 100 percent accuracy which will be less expensive and also this will require less time as well. There are [24] mainly three types of skin cancer. such as- basal cell carcinoma, squamous cell carcinoma and intraepidermal carcinoma. All these non-melanoma skin cancers are harmful for the human body. To identify the type, medical science is now using different types of analytical methods. Datasets help the scientists to benchmark and then differentiate the types of cancer in the skin. Raw image data and segmentation masks are maintained in the repository. The images are in their original resolution in the 1x directory, with 290 histology images in TIFF format in the Images directory and their respective segmentation mask in PNG format in the Masks directory. The photos are labeled with their diagnostic class and number, for example, BCC 25.png. To run this experiment, My lab pathology provides all types of helps. Here, they chose 290 slides in conjunction with a pathologist to represent typical basal cell carcinoma (140), squamous cell carcinoma (60), and intraepidermal carcinoma cases (90). Cases with unclear traits that necessitated a differential diagnosis were omitted. Shave biopsies (100), punch biopsies (58), and excisional biopsies are all included in the data (132). A pathologist then handannotated the tissue slice on the slide that best represented the diagnostic class for each slide. In late 2017 and early 2018, these tissue sections were scanned during a four-month period. The photos that arise pertain to patients between the ages of 34 and 96, with a median age of 70. Deep learning method makes the medical science now easier to identify the problems.

Chapter 3

Different types of skin cancer

3.1 Actinic Keratoses

Actinic keratosis and Bowens disease are skin disorders that [5] develop as a result of UV exposure. Sun-exposed regions including the face, ears, scalp, backs of the hands, and lower legs are the typical places to get it. These might occasionally be itchy or painful, or they can be absolutely painless and have no symptoms at all. The most typical neoplastic skin lesion is actinic (solar) keratosis, an intraepidermal squamous tumor of sun-damaged skin. Three grades have been proposed, and support for this division is growing, not least because of the potential therapeutic benefits. In 5–10% of individuals and in 30% of those who have immunosuppression, invasive squamous cell carcinoma is observed to develop. An instance of squamous cell carcinoma in situ of the skin and mucocutaneous junction is Bowen’s disease. In instances of clonal type, it is crucial to distinguish between clonal seborrheic keratosis and Paget’s disease from bowenoid papulosis, an HPV-associated lesion, actinic (solar) keratosis grade III, and intraepidermal poroid lesions. The clinical and histomorphological aspects of keratoacanthoma are now regarded consistently as those of a highly differentiated cutaneous squamous cell carcinoma. In terms of the clinical process, keratoacanthoma can spontaneously resolve. Anatomically, there is a distinctive development pattern as well as several regressive phases. The whole material is necessary for the final histomorphological diagnosis. Going to follow basal cell carcinoma in terms of frequency, squamous cell carcinoma of the surface is the second most widespread kind of skin cancer. The subtyping of cutaneous squamous cell carcinoma is crucial with regard to recurrences and the risk of metastasis. The American Joint Committee on Cancer (AJCC) categorisation additionally takes into account so-called increased traits in the staging across phases I and II, while the classification system of the Union Internationale Contra le Cancer (UICC) is purely based on physical spread.

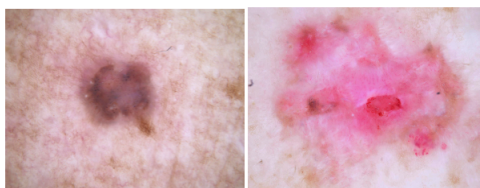


Figure 3.1: Actinic Keratoses

3.2 Basal Cell Carcinoma

The most prevalent kind of skin cancer is basal cell carcinoma,[2] and roughly 20% of Americans may have one of these lesions at some time in their life. If individuals don't receive it and aren't treated, it can enter the brain, damage nerves, and affect the facial bones. It often begins off being red or skin-colored, and its borders may or may not be rolled pearls. The boundaries eventually roll up as they become larger. A kind of skin cancer that originates in the basal cells is identified as basal cell carcinoma (BCC). The skin has normal basal cells lining it. They are the human cells that regenerate skin tissue. On the top layer of the skin, tumors occur as a result of basal cell cancer. These tumors frequently resemble lumps, ulcers, growths, marks, or red patches. BCC can nevertheless cause deformity despite the fact that it hardly ever metastasizes (spreads to other parts of the body). Rarely, it may extend to different bodily areas. When it does, it may even endanger life.

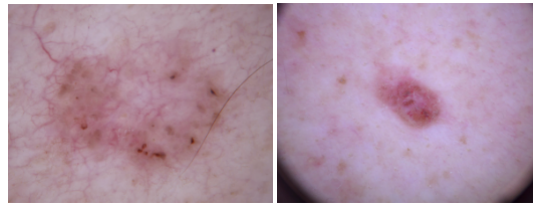


Figure 3.2: Basal Cell Carcinoma

3.3 Benign Keratosis-like Lesion

Seborrheic keratoses and solar lentigo are both considered to be types of benign keratosis.[3] Among acquired benign tumors, seborrheic keratoses and solar lentigo are most prevalent. With age, their frequency rises. 12% of the patients are between the ages of 15 and 25, while 100% of the adults are over 75. A typical benign skin disease called seborrheic keratosis, it most frequently appears on the forepart and torso. Typically, the lesions manifest as many, well-circumscribed, "stuck-on" pale to black plaques. The plaques may subsequently grow elevated and have a verrucous texture. Most lesions have a diameter of no more than 1 cm. The lesions often cause no discomfort and don't need any therapy. Even though various kinds of seborrheic keratosis do not distinguish clinically, there are five main histologic features that can be distinguished.

3.4 Dermatofibroma

Dermatofibromas grow most frequently on the lower legs. Their diameter ranges from 0.5 to 1.0 cm, and they move freely. Generally smooth, though sporadically scaly on the skin's surface. If you pinch the skin above, it may be tethered and

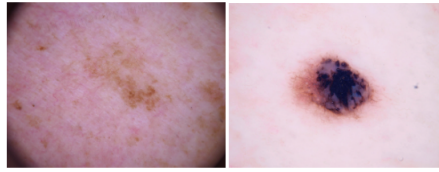


Figure 3.3: Benign Keratosis-like Lesion

produce a dimple. From skin-colored to pinkish, red, cream, white, and brown, the skin's tone varies. A person may have several dermatofibromas, which can develop at any place on the skin. Small, spherical, noncancerous surface formations are called dermatofibromas. The dermis, epidermis, and subcutaneous adipose cells are among the skin's multiple layers. Dermatofibromas also form when specific tissues in the dermis, its second layer of skin, regrow. Throughout this sense, dermatofibromas are benign (noncancerous) and safe. It is thought to be a typical skin tumor that certain patients potentially develop several times. The dermis section of the skin's dermis layer experiences an overgrowth of a variety of distinct cell types, which results in dermatofibromas. It is unknown why such expansion takes place. The developments frequently appear after a minor skin damage, such as a pin or insect bite that punctures the epidermis.

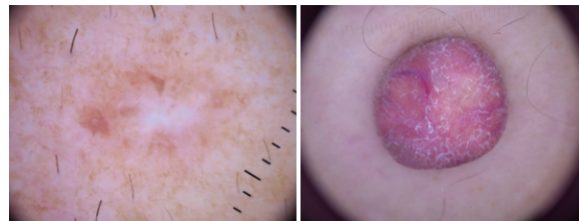


Figure 3.4: Dermatofibroma

3.5 Melanoma

The most serious kind of skin cancer is melanoma, which means “black tumor”. It can migrate to any tissue and develops aggressively. Melanocytes, which are skin cells, are the source of melanomas. Tissue seems to be where melanoma often develops in most cases. In particular, it starts in cells referred to as melanocytes. They're the melanin-producing cells. The pigment melanin is responsible for the shade of the skin, eyes and hair. Melanin, the dark pigment that gives skin its color, is formed by these cells. The majority of melanomas are black or brown in appearance, however some are pink, red, purple, or skin-colored. The majority of melanomas start in normal skin, however around 30% start in pre-existing moles. So because the majority of melanomas don't develop as moles, it is particularly crucial to be aware of developments in skin. Additional spread over a period melanoma types can develop in the vagina, nose, eyes, or the membranes lining those structures. An irregular mole or patch on skin that looks like it is developing or transforming over time is the most typical melanoma warning sign. Melanoma frequently

has a wavy or uneven margin. It could not resemble other skin discolorations. The location can be one you've had for a while or it might be a brand-new one.

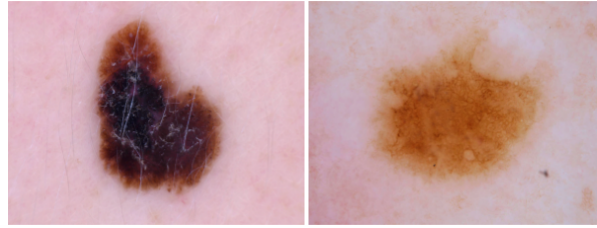


Figure 3.5: Melanoma

3.6 Melanocytic Nevus

The benign tumor known as a melanocyte-based nevus is called a melanocytic nevus and is not malignant. In the lower layer of the epidermis of the skin, the human ear, the sight, and other tissues, melanocytes are the cells that produce melanin. In skin pigmentation, they play a role. Acquired melanocytic nevi are more common throughout the first several years as an adult even if they are not present at birth. But the fourth and the fifth centuries had the highest incidence rates. Incidence dropped with each succeeding decade, and in those over 50, it is now extremely uncommon.

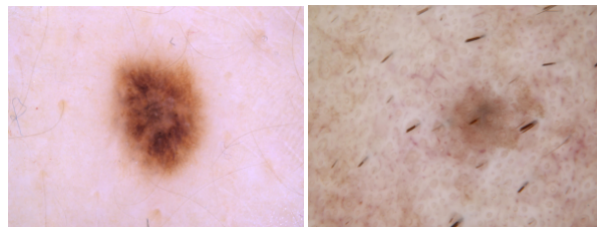


Figure 3.6: Melanocytic Nevus

3.7 Vascular Lesions

The dataset includes a variety of vascular skin lesions, including cherry angiomas, angiokeratomas, and pyogenic granulomas. This category also incorporates hemorrhage. Dermatoscopically, angiomas are recognizable by their red or purple hue and by solid, well-defined formations known as red collods or lacunes.

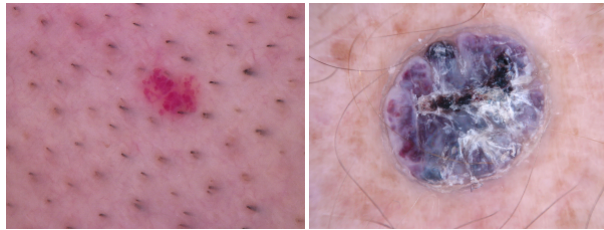


Figure 3.7: Vascular Lesions

Chapter 4

Research Methodology

4.1 Proposed Workflow

Here we can see that ,at first we have collected the dataset. Then there the dataset is being splitted into train and test folder in 90:10 ratio. Then again we splitted the train folder into train:validation as 70:30. Moreover, we train the train and validation set by four CNN models. Then after training we ensemble the models by the test data which gives us the predicted values of each image and gives us the mean predicted values. We also use ensemble in the K Nearest Neighbor algorithm that gives us the final accuracy .

4.2 Dataset

4.2.1 Dataset Details

We have used the ‘HAM10000’ dataset [9] that contains 10015 images of seven skin lei-son types. They are Actinic keratoses, Basal Cell Carci-noma, Benign Keratosis-like lesions, Dermatofibroma, Melanoma, Melanocytic Nevi and Vascular Lesions. Figure 4.2 shows samples from classes of Actinic keratoses, Basal Cell Carci-noma, Benign Keratosis-like lesions, Dermatofibroma, Melanoma, Melanocytic Nevi and Vascular Lesions starting from left to right.

Name	Number of images
Actinic Keratoses	327
Basal Cell Carci-noma	514
Benign Keratosis-like Lesions	1099
Dermatofibroma	115
Melanoma	1113
Melanocytic Nevi	6705
Vascular Lesions	142

Table 4.1: Skin cancer names

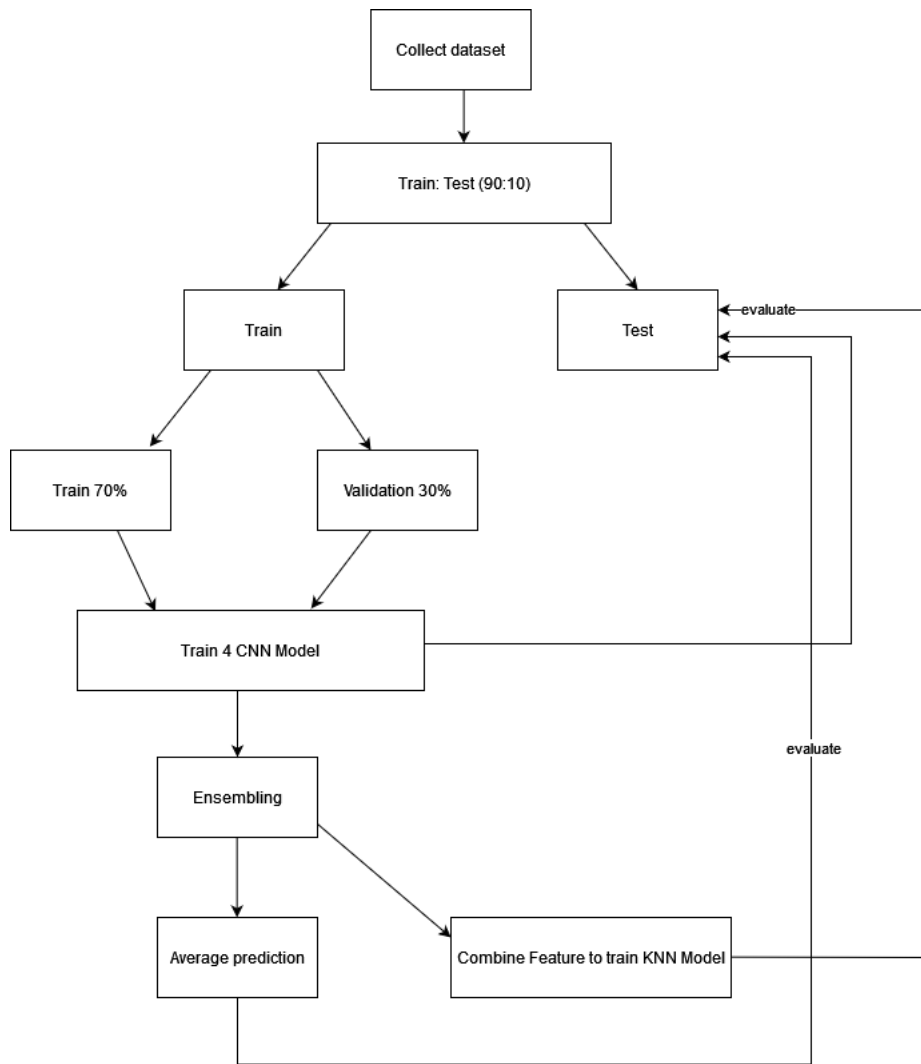


Figure 4.1: Working procedure

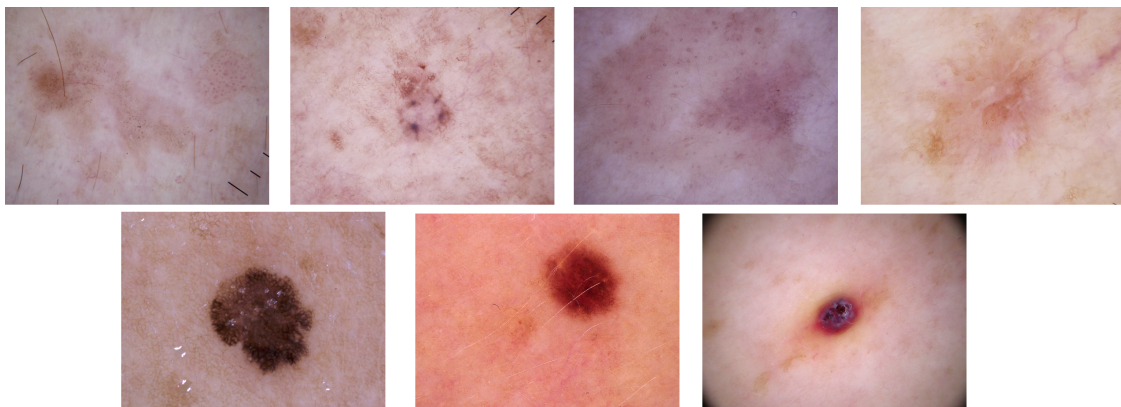


Figure 4.2: Dataset Samples

4.2.2 Dataset Augmentation

We have then augmented our training images by rotating, translation, vertical flip, horizontal flip and shear. The total number of images in the training set after performing data augmentation is 37854 images. Figure ?? shows example images after performing data augmentation.

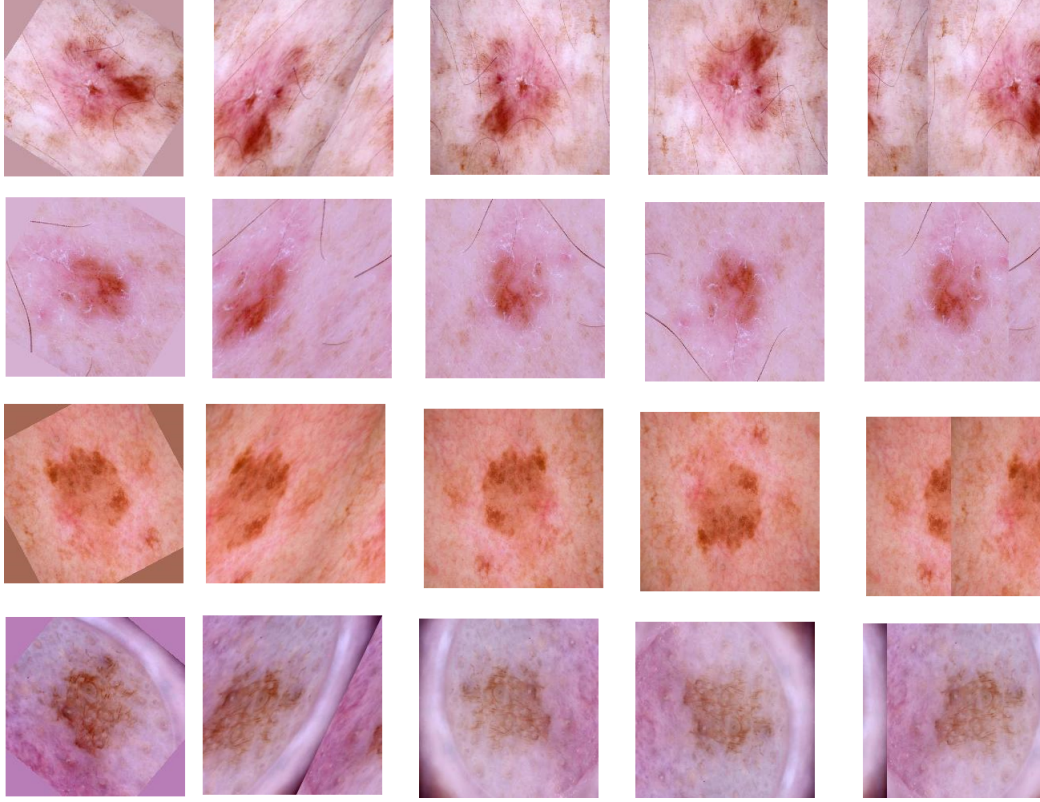


Figure 4.3: Data Augmentation

4.2.3 Dataset preprocessing

First of all, we resize all the images into $224 \times 224 \times 3$ size. Following that, we divided the image values by 255 to normalize the values between 0 and 1. Then we split these images into train and test with the ratio of 90:10. After that, there will be 9013 images to train our pertained model. These 9013 images will then be split into train and validation and the ratio will be 70:30. So after splitting all the images the train class will now have 6309 images, the validation class will have 2704 images and the test class will have 1002 images.

4.3 CNN Models

4.3.1 EfficientNetV2

EfficientNetV2S [23] is basically a smaller and a newer edition of EfficientNetV2 with fewer parameters. As our topic indicates we tried to build an efficient model to detect skin cancer with the help of image data. So we want our model to be more

Name	label
Actinic keratoses	0
Basal cell carci-noma	1
Benign keratosis-like lesions	2
Dermatofibroma	3
Melanoma	4
Melanocytic nevi	5
Vascular lesions	6

Table 4.2: Labeling dataset

accurate and use less computational power. EfficientNetV2S has 21.6 Million parameters which is less compared to previous versions of EfficientNet. EfficientNetV2 uses progressive learning which means that at first when image sizes are initially small when the training-starts, they progressively size up over time. Training rate of EfficientNet and image size are inversely proportional. Besides that, the performance also decreased because of progressive learning. Increasing the regularization and image sizes dynamically is a solution to this problem. “Depth wise convolutional layer” is used by EfficientNet, which has less parameters and FLOPS but on the other hand, it can not unleash the full potential of modern accelerators(CPU/GPU). Fused MB-Conv layer is the solution to this existing problem. To make it more efficient, the old MB Conv layers have been replaced with Fused MB-Conv layer. We use training-aware NAS to adaptively figure out the ideal ratio of fused and conventional MB Conv layers. Early on, performance with smaller models is enhanced by replacing some of the MB Conv layers with fused layers, according to the findings of NAS. Additionally, it demonstrates the benefit of having a lesser expansion ratio for the MB Conv layers (across the network). Finally, it is preferable to have relatively small kernel sizes with more layers. The authors declared this process is not necessary to improve performance. So that Non-uniform scaling method is used in later phases which add more layers. EfficientNet also set a limit of maximum image size because of the tendency to scale up images aggressively. EfficientNetV2 is trained up to 11 x faster while being 6.8 times smaller than EfficientNetV1. Here, we have used the implementation of EfficientNetV2S from keras library.

4.3.2 DenseNet121

DenseNet121 [8] is one of the models in the keras applications that has Top-1 accuracy of 75 percent and Top-5 accuracy of 92.3 percent. Having said that it has also the parameter count 8.1M . It is seen that , if the convolutional network has the shorter connection between the layers closer to the input and close to the output , it can be more deeper, efficient to train and more accurate. Through this knowledge, DenseNet comes to light with its Dense Convolutional layer where it connects every layer to every other layers in a feed forward fashion. On the other hand it is seen from the previous convolutional neural network is that conv networks with L layers have L connections .The DenseNet has many advantages . For instances : It can remove the vanishing gradient problem , strengthen the feature propagation , encourage the feature reuse and it can also reduce the features thats what makes it special .

4.3.3 InceptionNetV3

Since 2014, convolutional networks have become more widely used, it has resulted in significant gain across multiple benchmarks. But to ensure higher accuracy the computational cost has already gone up so much that it has become a barrier to achieve more accuracy. On the ILSVRC 2012 benchmark classification problem, it outperformed Google Net, VGGNet, PReLU, etc. architectures with a significantly lower computational cost. InceptionNetV3 is a CNN based network for classification. Another name for it is the Google Net architecture. It uses inception modules, which are 48 layers deep and consist of a concatenated layer with 1×1 , 3×3 and 5×5 convolutions. The output of the inception module is created by stacking the parallel features that were extracted depth-wise. It decreases the number parameters significantly and boosts up training speed. InceptionNetV3 [7] has only 23.9M parameters which is very small compared to other CNN models. InceptionNetV3 has the Top-1 accuracy of 77.9 percent and Top-5 accuracy of 93.7 percent.

4.3.4 Ensembling

It is a procedure that helps to improve the performance and results of the combining model used. Ensemble models have multiple base models however it acts as one single model. It basically processes the multiple models to predict an outcome. It can do this by different model algorithms or by using different training dataset.

Chapter 5

Experiments and Results

On this work, we initially ran four different convolutional neural network architectures, which are EfficientNetV2B3, EfficientNetV2S, InceptionNetV3 and DenseNet121. Furthermore, we ensembled the models through averaging the predictions and based on a K-Nearest Neighbors approach where we used features from all the models to train a separate KNN model. We also evaluated the models using Explainable AI by using the Lime library.

5.1 Experiment With EfficientNetV2B3

On our first experiment with convolutional neural network, we ran the EfficientNetV2B3. The model was ran with batch size set to 32, learning rate set to 10^{-5} . We loaded the weights from the model trained on ImageNet dataset using Keras library and we ran the model for 50 epochs. Figure 5.1 shows the training and validation losses of the model and Figure 5.2 shows the training and validation accuracies of the model during the training process. We used Keras Checkpoint to save the model with the highest validation accuracy resulting in 0.8295 and further used the best model to evaluate on the testing set. The model achieved an accuracy of 83% on the testing set. We have shown the Precision, Recall and F1 Scores in table ?? for all the classes on the testing set for the model. Again, we have shown the confusion matrix on the testing set for each of the classes on Figure 5.3, where class 0 indicates Actinic Keratoses, class 1 indicates Basal Ccell Carci-noma, class 2 indicates Benign Keratosis-like lesions, class 3 indicates Dermatofibroma, class 4 indicates Melanoma, class 5 indicates Melanocytic Nevi, class 6 indicates Vascular Lesions.

Class	Precision	Recall	F1-score
Actinic keratoses	0.67	0.73	0.70
Basal cell carci-noma	0.61	0.75	0.67
Benign keratosis-like lesions	0.65	0.67	0.66
Dermatofibroma	0.50	0.67	0.57
Melanoma	0.68	0.55	0.61
Melanocytic nevi	0.92	0.92	0.92
Vascular lesions	0.73	0.79	0.76

Table 5.1: EfficientNetV2B3 Precision, Recall and F1-score

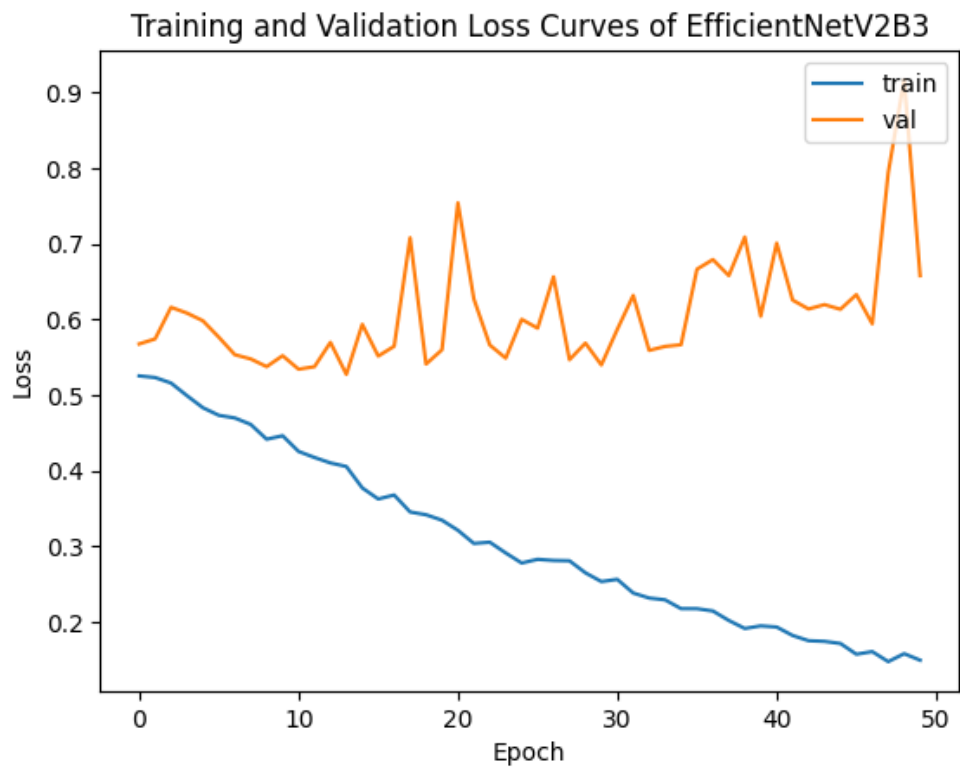


Figure 5.1: Training and validation loss curve of EfficientNetV2B3

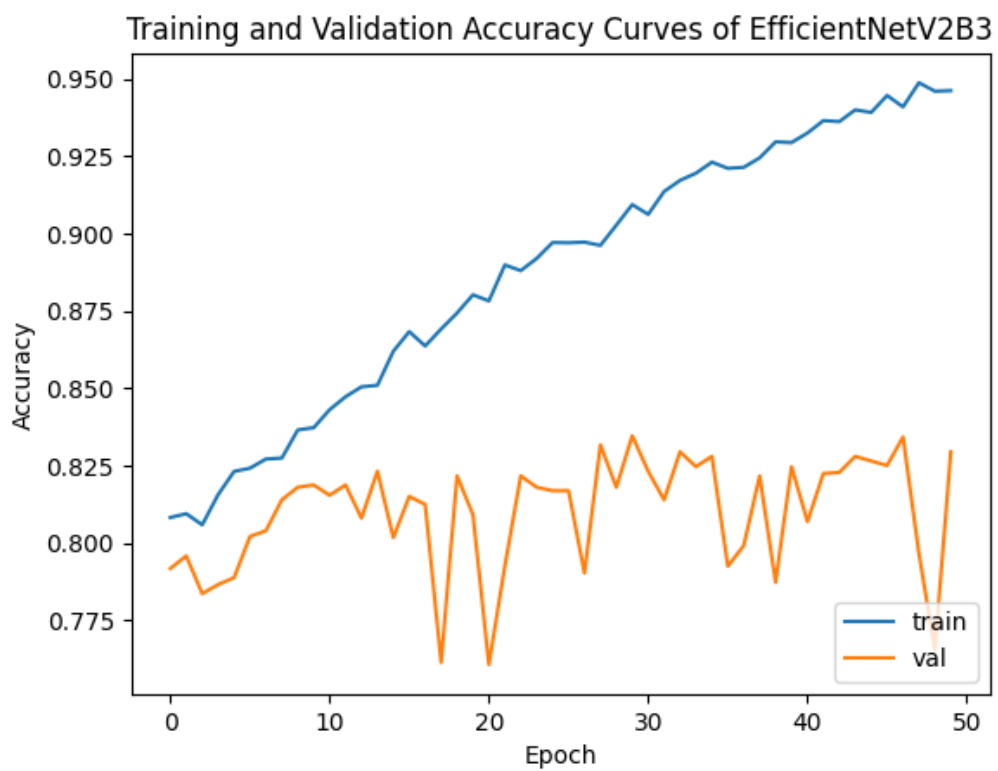


Figure 5.2: Train validation accuracy curve of EfficientNetV2B3

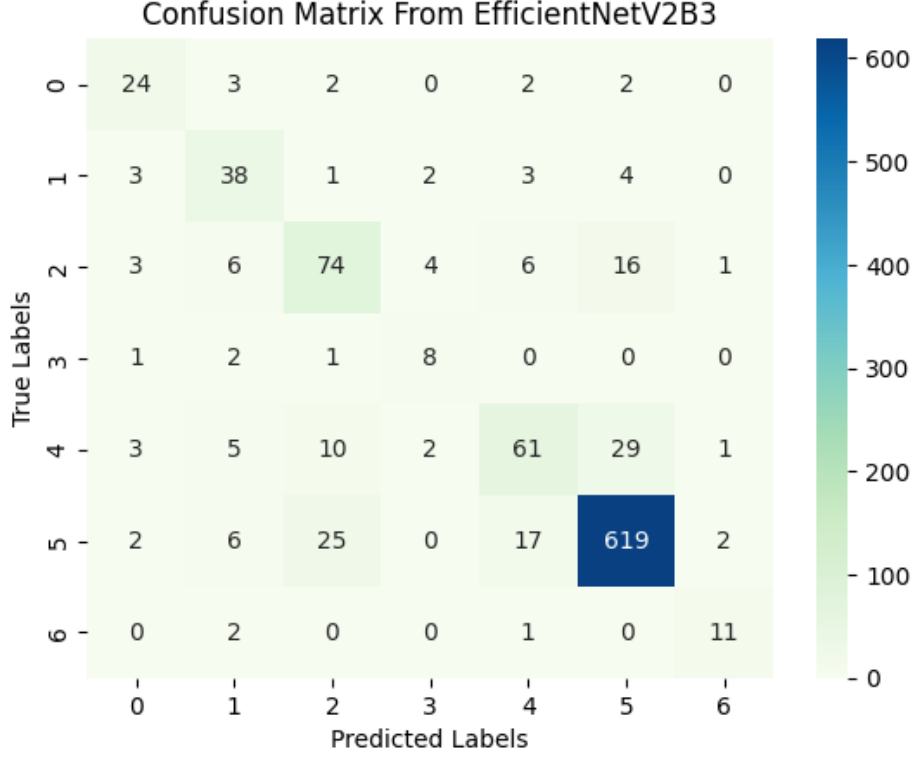


Figure 5.3: Confusion Matrix of EfficientNetV2B3

5.2 Experiments with EfficientNetV2S

Furthermore, we ran another CNN model called EfficientNetV2S which belongs to the family of EfficientNetV2, an improved version of EfficientNet. The 'S' in EfficientNetV2S variant stands for 'Small'. The model was also ran with a batch size set to 32, learning rate set to 10^{-5} for 50 epochs and the model with highest validation accuracy was saved to evaluate on testing set. Figure 5.4 shows the training and validation losses of the model and Figure 5.5 shows the training and validation accuracies of the model during the training process. The model achieved a maximum validation accuracy of 0.8609. Again, when evaluating on the testing set the model achieved an accuracy of 86% on the testing set, performing better than EfficientNetV2B3. We have shown the Precision, Recall and F1 Scores in table X for all the classes on the testing set for the model. Again, we have shown the confusion matrix on the testing for each of the classes on Figure 5.6, where class 0 indicates Actinic Keratoses, class 1 indicates Basal Cell Carci-noma, class 2 indicates Benign Keratosis-like lesions, class 3 indicates Dermatofibroma, class 4 indicates Melanoma, class 5 indicates Melanocytic Nevi, class 6 indicates Vascular Lesions.

Class	Precision	Recall	F1-score
Actinic keratoses	0.58	0.67	0.62
Basal cell carci-noma	0.70	0.82	0.76
Benign keratosis-like lesions	0.79	0.68	0.73
Dermatofibroma	0.73	0.67	0.70
Melanoma	0.71	0.55	0.62
Melanocytic nevi	0.92	0.96	0.94
Vascular lesions	0.79	0.79	0.79

Table 5.2: EfficientNetV2S Precision, Recall and F1-score

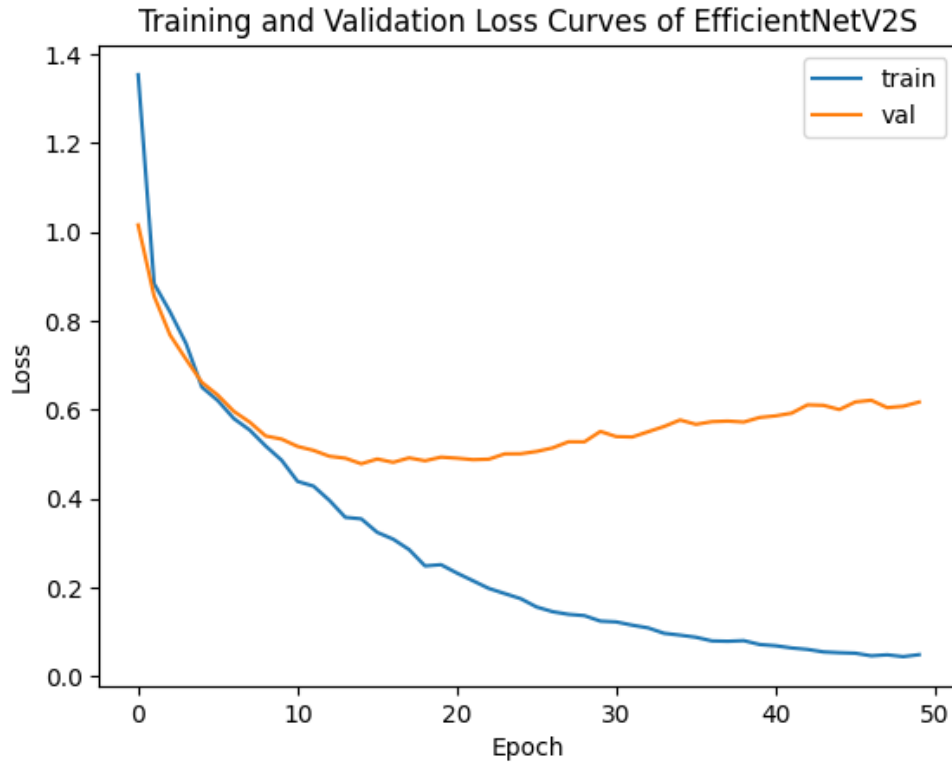


Figure 5.4: Training and Validation loss curve of EfficientNetV2S

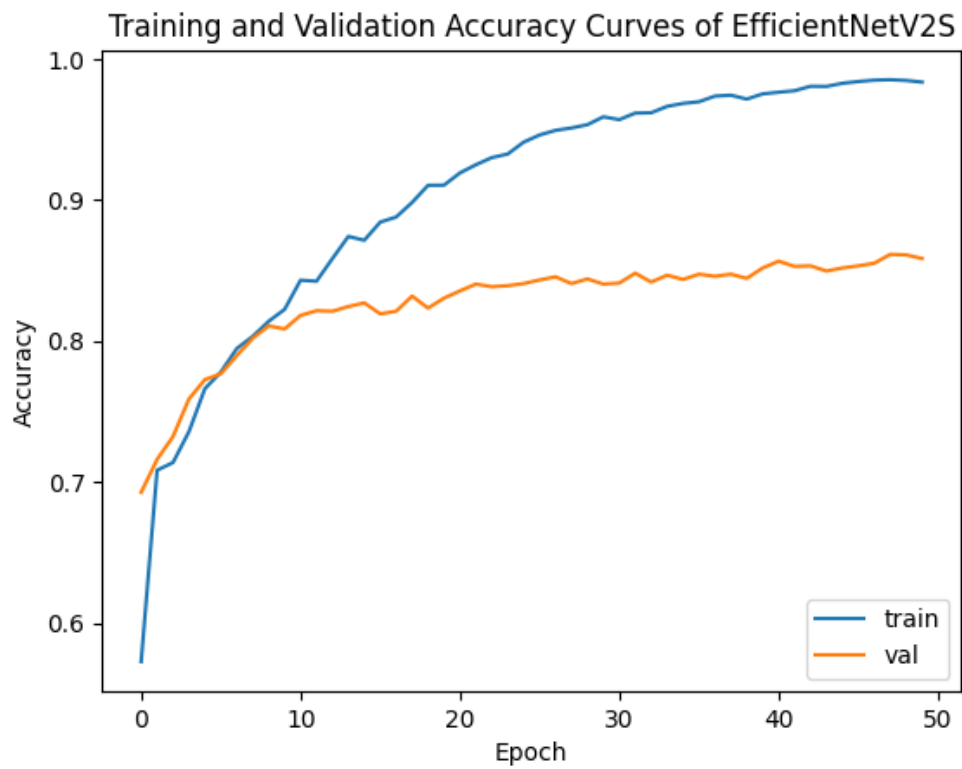


Figure 5.5: Training and Validation accuracy curve of EfficientNetV2S

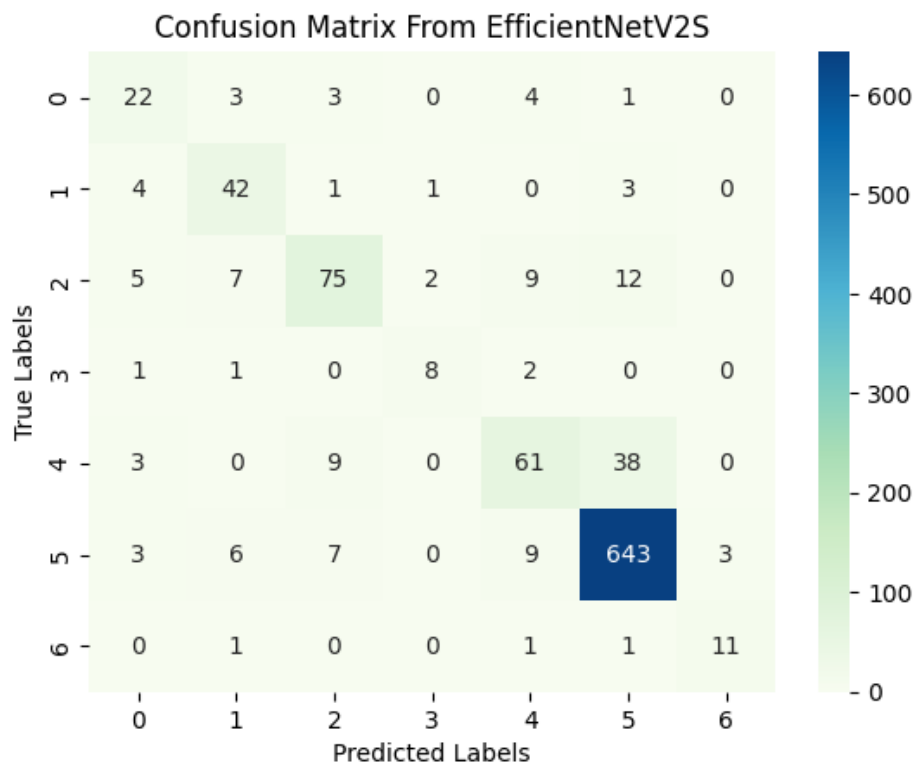


Figure 5.6: Confusion Matrix of EfficientNetV2S

5.3 Experiments with InceptionNetV3

The third convolutional neural network model that we ran on our experiments was InceptionNetV3. The model was ran with same hyperparameters as our previous experiments with CNN architectures, which are batch size set to 32, learning rate set to 10^{-5} and was run for 50 epochs. The best model achieved a validation accuracy of 0.8306 and was saved to evaluate on the testing part of the dataset. InceptionNetV3 achieved a testing accuracy of 84%, performing better than EfficientNetV2B3 while struggling behind EfficientNetV2S. The training and validation accuracy curves are shown in Figure 5.8, the training and validation loss are shown in Figure 5.7. The Preceision, Recall, and F1 Scores for each of the classes are shown on Table 5.3 and finally the confusion matrix for testing set is shown on Figure 5.9 where class 0 indicates Actinic Keratoses, class 1 indicates Basal Cell Carci-noma, class 2 indicates Benign Keratosis-like lesions, class 3 indicates Dermatofibroma, class 4 indicates Melanoma, class 5 indicates Melanocytic Nevi, class 6 indicates Vascular Lesions.

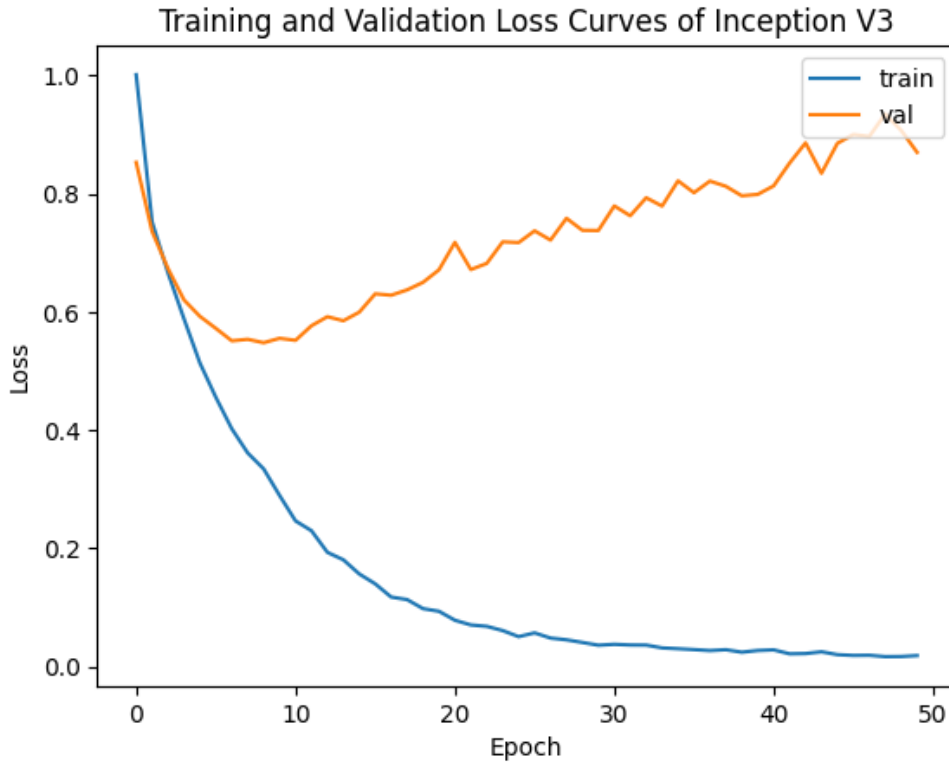


Figure 5.7: Training and Validation loss curve of InceptionNetV3

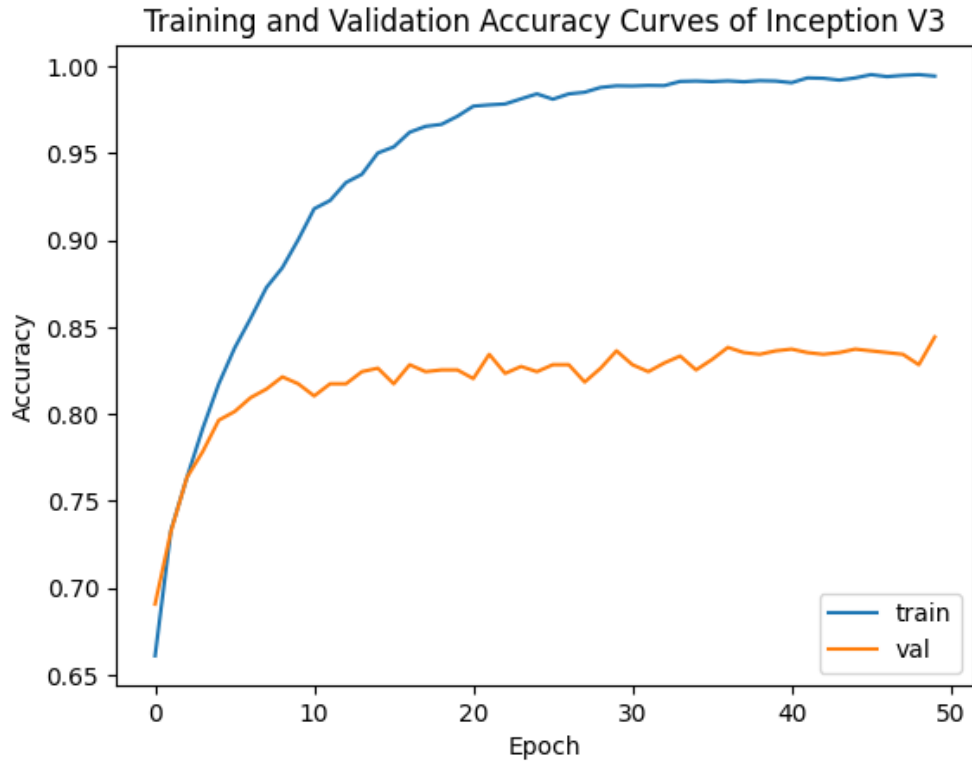


Figure 5.8: Training and Validation accuracy curve of InceptionNetV3

Class	Precision	Recall	F1-score
Actinic keratoses	0.62	0.64	0.63
Basal cell carci-noma	0.79	0.75	0.77
Benign keratosis-like lesions	0.73	0.66	0.70
Dermatofibroma	0.58	0.58	0.58
Melanoma	0.78	0.48	0.59
Melanocytic nevi	0.88	0.96	0.92
Vascular lesions	1.00	0.71	0.83

Table 5.3: InceptionNetV3 Precision, Recall and F1-score

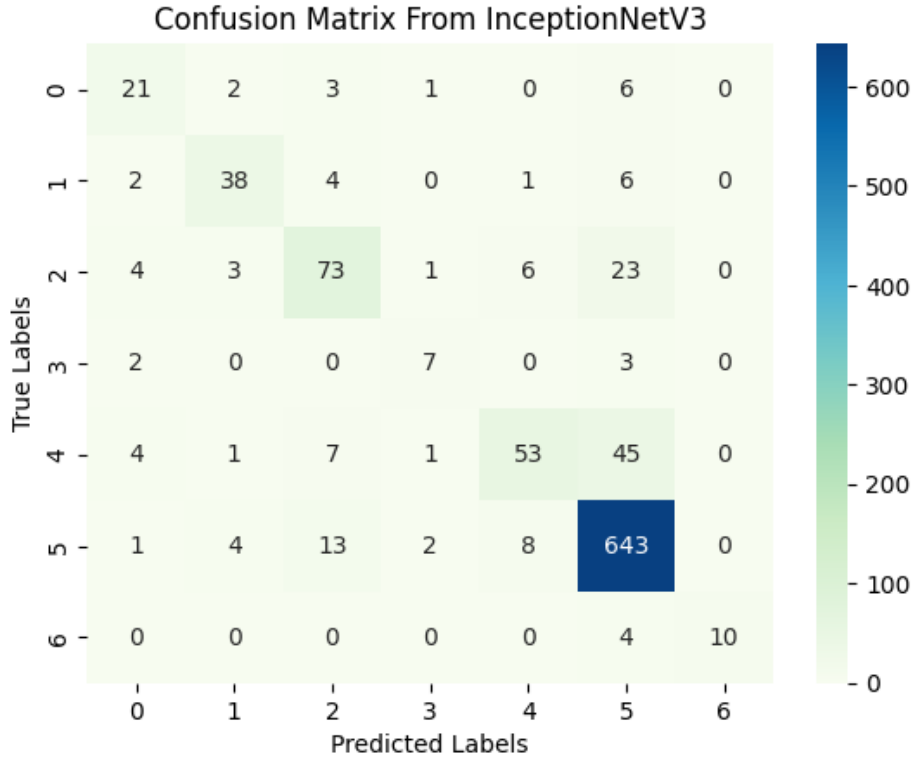


Figure 5.9: Confusion Matrix of InceptionV3

5.4 DenseNet121

The final CNN model that we ran on our experiments was DenseNet121. The model was again ran with the same hyperparameters as the previous experiments, where we set the learning rate to 10^{-5} and batch size to 32. The model was similarly ran for 50 epochs and the model with the highest validation accuracy was used to evaluate on the testing set. Compared to all the previous CNN models that we ran on this work, DenseNet121 had the highest accuracy of 88%. The training and validation loss curves are shown on Figure 5.11 and training and validation accuracy curves are shown on Figure 5.12. Furthermore, the confusion matrix on testing set for DenseNet121 is shown on Figure 5.13 and the Precision, Recall and F1 Scores are shown on Table ??.

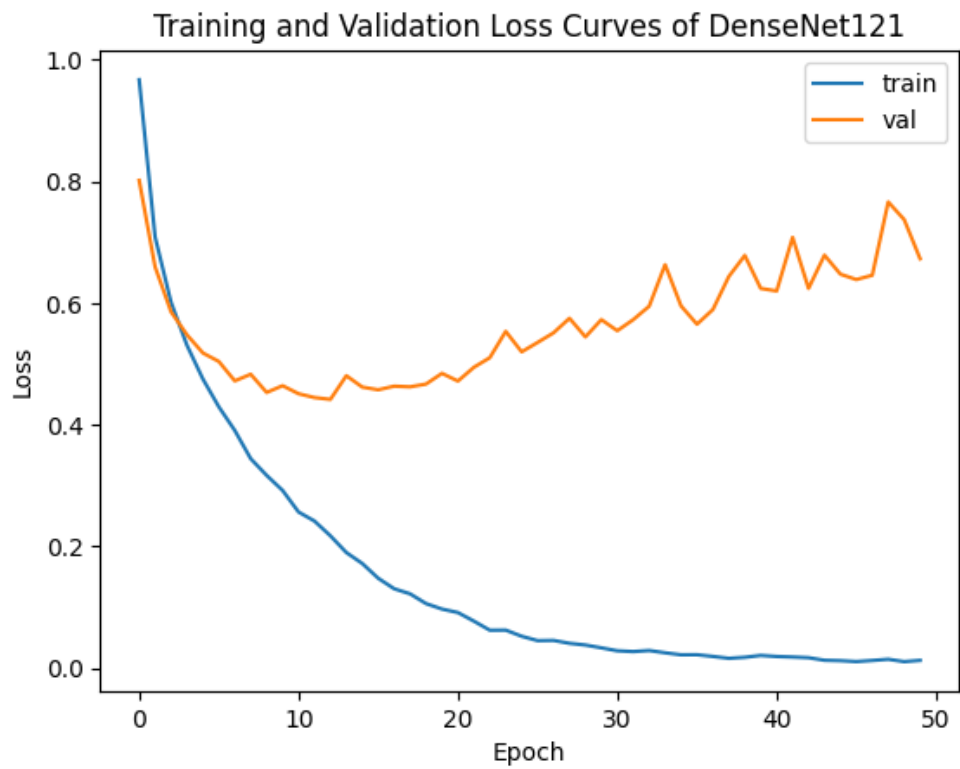


Figure 5.11: Training and Validation loss curve of DenseNet121

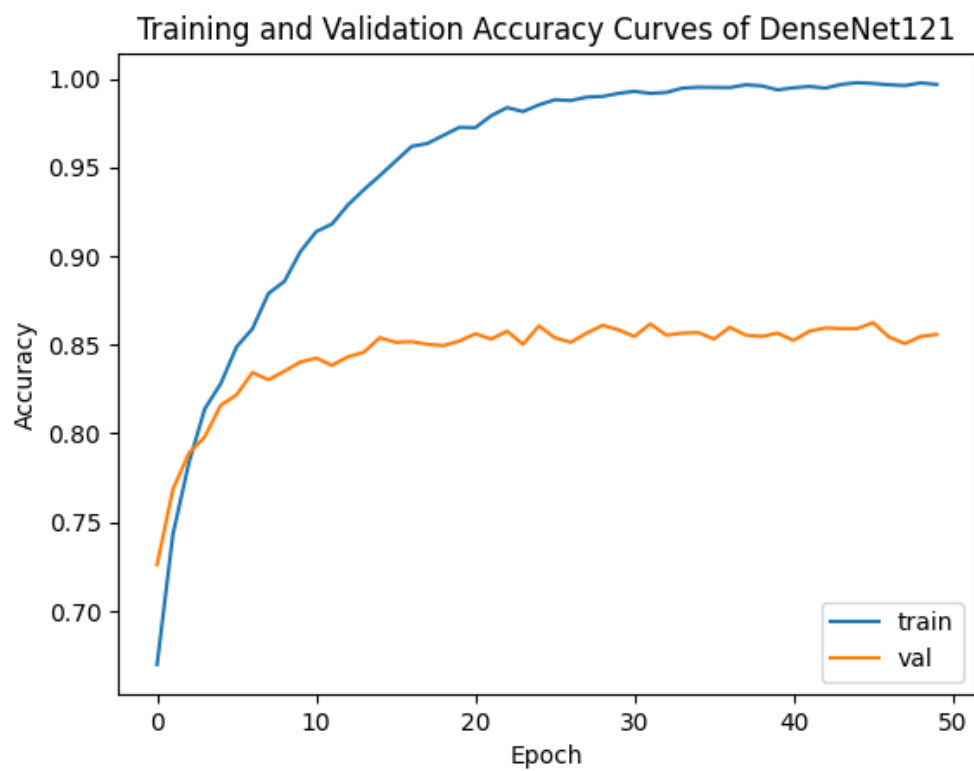


Figure 5.12: Training and Validation accuracy curve of DenseNet121

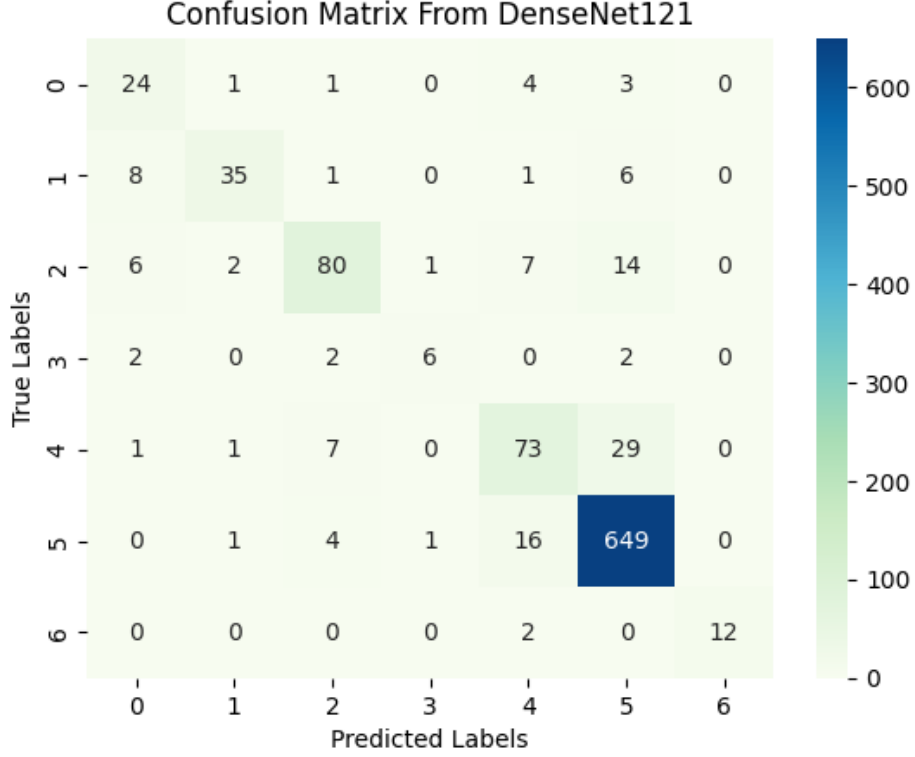


Figure 5.13: Confusion Matrix of DenseNet121

Class	Precision	Recall	f1-score
Actinic keratoses	0.59	0.73	0.65
Basal cell carci-noma	0.88	0.69	0.77
Benign keratosis-like lesions	0.84	0.73	0.78
Dermatofibroma	0.75	0.50	0.60
Melanoma	0.71	0.66	0.68
Melanocytic nevi	0.92	0.97	0.94
Vascular lesions	1.00	0.86	0.92

Table 5.4: DenseNet121 Precision, Recall and F1-score

5.5 Ensemble Through Mean Prediction

Better results can be achieved through averaging the predictions from different deep learning models. On this paper, we used four different convolutional neural network models which are EfficientNetV2B3, EfficientNetV2S, InceptionNetV3 and DenseNet121. We initially predicted on the testing dataset for each of the models. Since the models have a Dense layer with 7 units as the last layer of the model with Softmax activation, the models would return a 1-D matrix with probability for all the seven classes. The predictions from all of the four models are then averaged to get a final mean result. Figure 5.14 shows the overview of how the operation is performed. The averaged prediction achieved a higher accuracy than each of the models individually, reaching an accuracy of 90% on the testing set. Table ??

shows the results on testing set after performing ensemble through averaging the predictions of the four models.

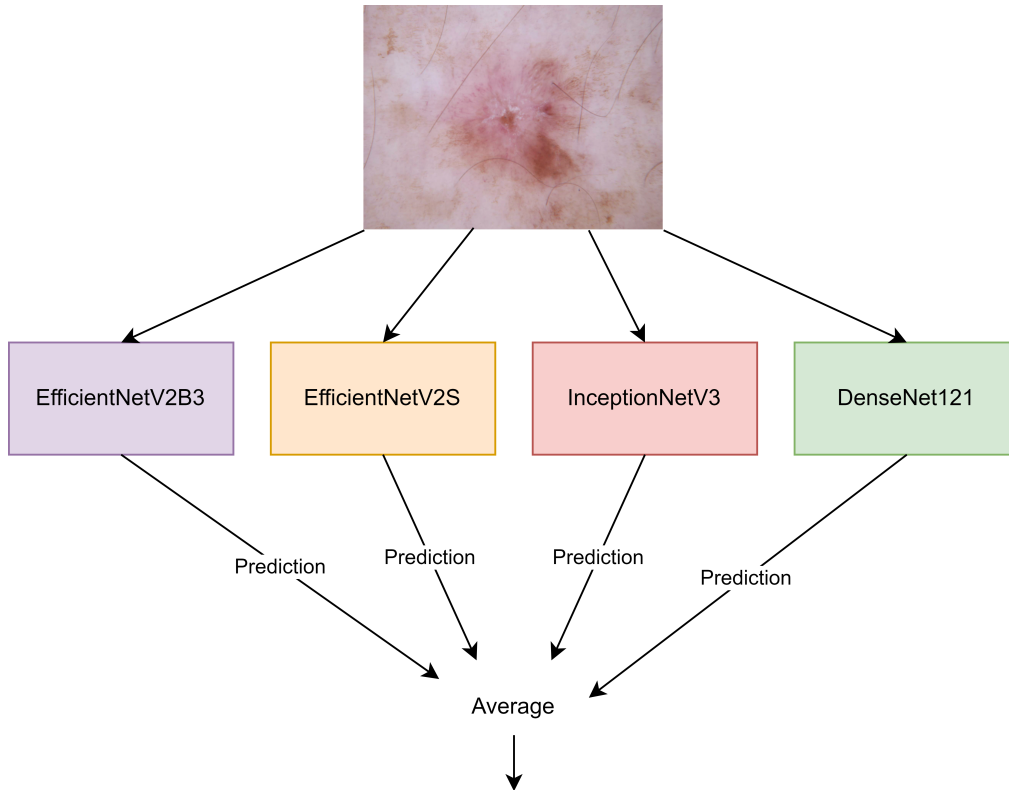


Figure 5.14: Ensemble through Mean Predictions

Class	Precision	Recall	f1-score
Actinic keratoses	0.71	0.73	0.72
Basal cell carci-noma	0.81	0.90	0.85
Benign keratosis-like lesions	0.88	0.76	0.82
Dermatofibroma	0.89	0.67	0.76
Melanoma	0.84	0.69	0.69
Melanocytic nevi	0.92	0.98	0.95
Vascular lesions	0.93	0.93	0.93

Table 5.5: After ensembling the Precision, Recall and F1-score

5.6 Ensemble Based on K-Nearest Neighbors

On this approach, the fully-connected or dense layers after the GlobalAveragePooling2D layer on each of the four trained convolutional neural network models were removed. As a result, when an image was used to predict using the models, instead of returning the probability for each of the 7 classes that were produced on the previous experiments, it would output or extract the features that are produced in the GlobalAveragePooling2D layer. The EfficientNetV2B3 model's GlobalAveragePooling2D layer would return a 1-D matrix with 1536 elements, the EfficientNetV2S

would return a 1-D matrix of 1280 elements, InceptionNetV3 would return 1-D matrix of 2048 elements and DenseNet121 would return a 1-D matrix of 1024 elements. Since, the approach is dependent on K-Nearest Neighbors algorithm, which doesn't require any validation data unlike deep learning models, we treated both training and validation data as training data for training the machine learning model. In order to fit the KNN [1] model, we first extracted the features from GlobalAveragePooling2D layers from the training and validation images for each of the four models and concatenated all the features for all the training and validation images. In total the 37,854 images in training set and 2704 images in the validation were used to extract the features from all the CNN architectures. Furthermore, combining all the features for each of the model's GlobalAveragePooling2D layer, resulted in a 1-D matrix of 5888 elements and for total 40550 (training and validation) images' features produced a 2-D matrix of shape (40550, 5888). Finally, the features from training and validation images were used to fit the KNN model where we set the number of neighbors to 1. Again, the four CNN models were used to extract features from the 1002 testing images and their GlobalAveragePooling2D layer's features were concatenated, resulting in a 2-D matrix of shape (1002, 5888) for all the 1002 testing images. In the end, the KNN model was used to predict on the features extracted from testing set and in this case we managed to receive the highest accuracy of 92%, overcoming all the previous experiments we have performed on our paper. Figure 5.15 shows the process of training KNN model based on the features extracted from CNN models on training and validation set and Figure 5.16 shows the process of predicting using KNN model based on the features extracted from the CNN architectures. On the Figure 5.17, we visualised the features extracted from the GlobalAveragePooling2D layer for the four CNN models for different images, however for visualizing only, we didn't use the entire 1-D matrix to reshape into a 2-D matrix as it wouldn't reshape into a complete 2-D Square matrix. For this reason, we took as much as values possible from the features. Therefore, for visualizing purpose, on EfficientNetV2B3's GlobalAveragePooling2D layer, we took 1521 elements out of 1536 to reshape into a 39x39 matrix, for EfficientNetV2S' GlobalAveragePooling2D layer's features, we took 1225 elements out of 1280 to reshape into a 2-D matrix, for InceptionV3 we took 2025 elements out of 2048 for reshaping into a 45x45 2-D matrix and for DenseNet121 we used the entire feature to reshape into 32x32 2-D matrix and finally for the concatenated features having total 5888 elements, we took 5776 elements to reshape into a 2-D matrix of 76x76.

Class	Precision	Recall	F1-score
Actinic keratoses	0.79	0.84	0.81
Basal cell carci-noma	0.90	0.85	0.88
Benign keratosis-like lesions	0.79	0.93	0.85
Dermatofibroma	0.75	0.90	0.82
Melanoma	0.69	0.91	0.79
Melanocytic nevi	0.99	0.93	0.96
Vascular lesions	0.86	0.92	0.89

Table 5.6: After K-NN based ensembling the Precision, Recall and F1-score

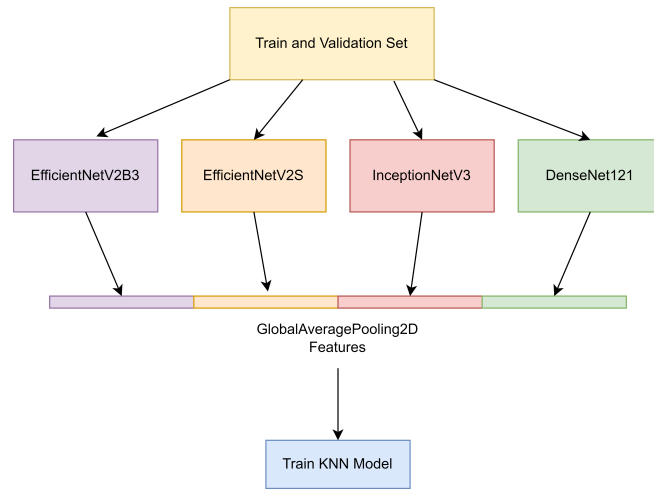


Figure 5.15: Process of Training KNN model through CNN Extracted Features

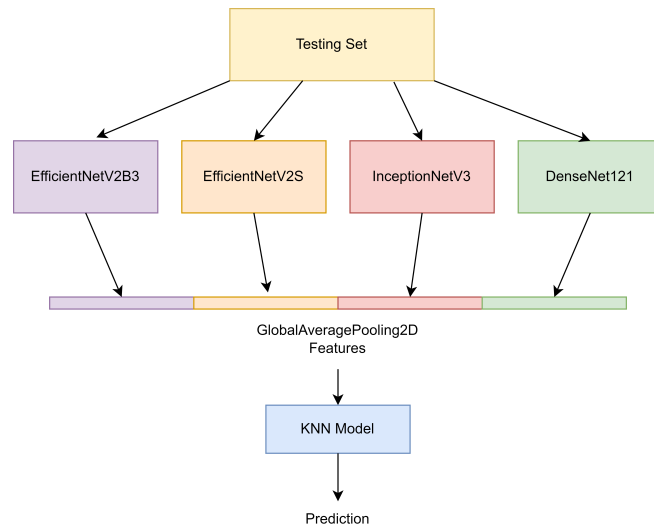


Figure 5.16: Process of Predicting using KNN model through CNN Extracted Features

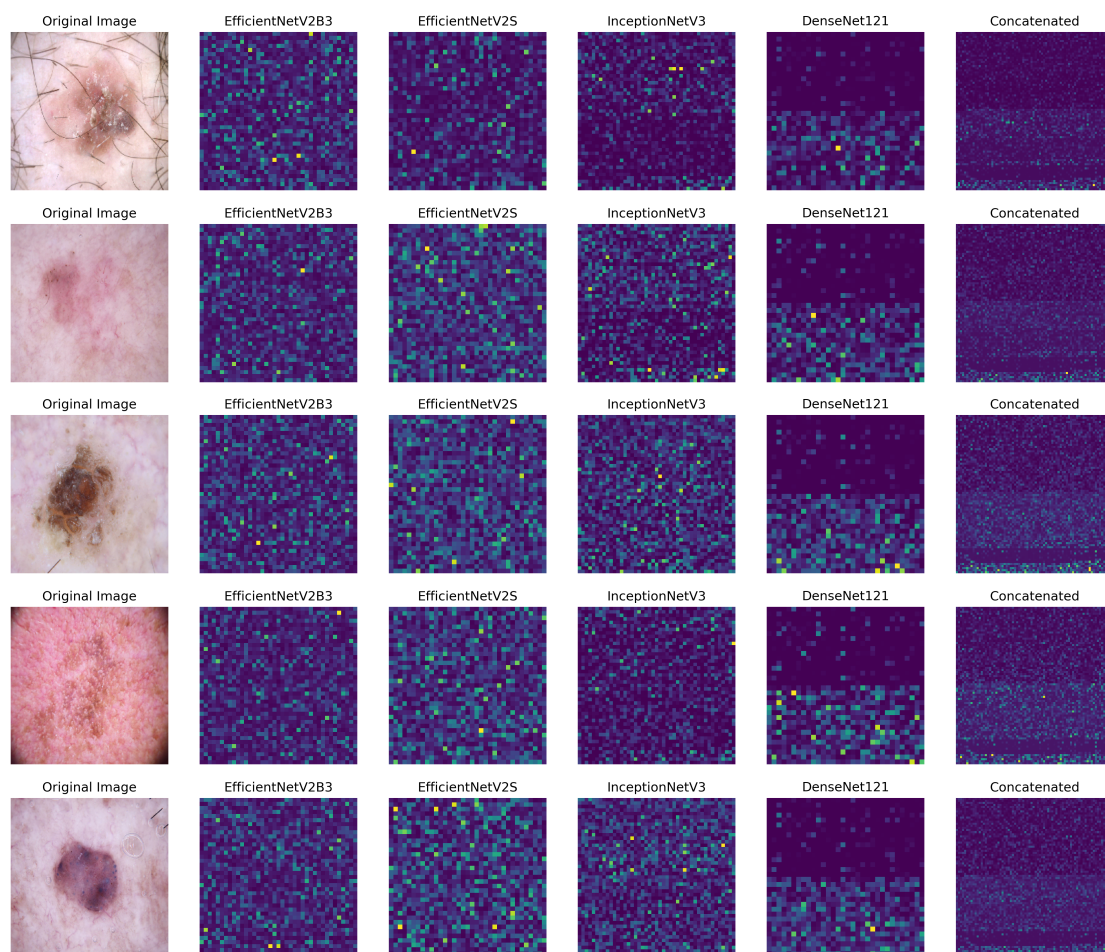


Figure 5.17: Features of GlobalAveragePooling2D layers for different models visualized in 2-D space

5.7 Explainable AI

We used the Lime library for Explainable AI for each of the four CNN models that we used in this experiment. Figure 5.18 shows the output of explainable AI where the yellow marked regions are the features the CNN models used to make the predictions.

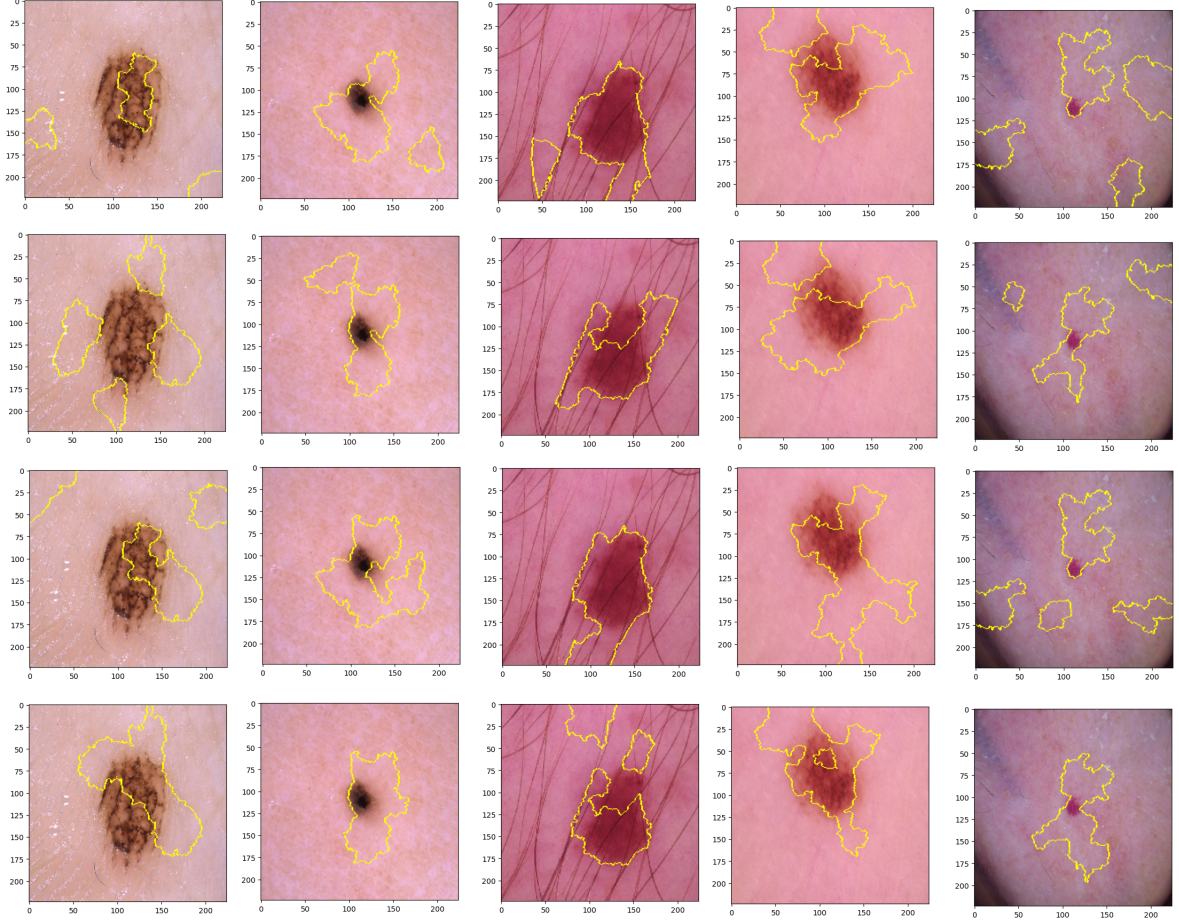


Figure 5.18: Explainable AI

5.8 Comparision with other papers

In our paper we have used the HAM 10000 dataset. Our accuracy after the ensemble of the four models gives an accuracy of 92% which is more than other papers that used the same dataset. (HAM10000) .For instance in the paper it has an accuracy of [19]90.51%,if we look at the paper.Then we can see that the paper[12] has an accuracy of 90%.So after reviewing papers of other author using this paper it is seen that many of them using different dataset with the dataset we used. However, our dataset accuracy with the papers using same dataset we get the highest accuracy of 92%.Here we used the four CNN models , ensemble it and then by using the K-Nearest Neighbour algorithm we get this accuracy that is not seen on other papers that used our same dataset .

Chapter 6

Conclusion

The number of people diagnosed with skin cancer is increasing day by day. Besides that, the number of deaths is also making this so alarming. Many people don't know about this so they ignore this thinking it is just another skin disease. Furthermore, the identification process also takes time which discourages people from testing if they are affected by this. Because of this problem that people are facing we have built a model where it will take just a few moments to test if the person is affected or not by the picture of their affected part. We have proposed some models which can be determined almost accurately by just only evaluating the picture of the affecting part. In the future, we will implement the algorithms that we have proposed to use and evaluate their accuracy. We believe that this will be an effective method which will save time and money of the people. In most cases it is seen that the cost is very high in order for the detection of the disease. So, researchers are always trying to make technologies more cost friendly so that it can be available to every part of the world population. The affordability of the cost are targeting to get reduced by using more efficient and accurate models in order to minimize the computational cost. So we are also planning to build certain models which will be helping us to get fulfill our target. By taking the models with the less amount of the parameters and certainly with the high top-1 accuracy we can be used so the computational cost get reduced and the model that we are proposing can give the best computational accuracy with less cost however having higher accuracy. The aims and objective of making such models comes from the necessity of the people around the globe and because of increasing amount of growing such disease

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