HAZRAT ALI CLASSIFICATION OF SKIN CANCER IMAGES USING CONVOLUTIONAL NEURAL NETWORK NEU 2019

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A THESIS SUBMITTED TO THE GRADUATE SCHOOL OF APPLIED SCIENCES OF NEAR EAST UNIVERSITY

By
HAZRAT ALI

In Partial Fulfillment of the Requirements for the Degree of Master of Science in Computer Engineering

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Approval of Director of Graduate School of Applied Sciences

Prof. Dr. Nadire ÇAVUŞ

We certify this thesis is satisfactory for the award of the degree of Master of Science in Computer Engineering

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I hereby declare that all information in this document has been obtained and presented in accordance with academic rules and ethical conduct. I also declare that, as required by these rules and conduct, I have fully cited and referenced all material and results that are not original to this work.

Name, Last Name:
Signature:
Date:

To all the patient suffering from skin Cancer…

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ABSTRACT

Skin cancer is a major problem nowadays all over the world and due to the technology era, it is important to solve the problem through machines instead of human. Deep learning is one of the best ways to solve the skin cancer problems. Deep learning is a new research area within the modern technology using micro services with big data, virtual reality and also augmented reality. Due to the development of huge computing capacity, technologies such as deep learning application using MobileNet(CNN) has revolutionized image classification. Deep learning can be used to classify the different types of skin cancer types. This learning technique uses different algorithms such as MobileNet CNN algorithms. MobileNet algorithms are the suitable ways to recognize the images from the input and gives accurate results. In this current work Mobilenet CNN is used to our data set to classify skin diseases types according to our input.

The study showed that the implementation of Deep learning within the field of cancer diseases can be the most suitable way to classify and recognized skin cancer images, which can be very beneficial in the field of medicine for early diagnosis and improve the accurate diagnosis result. This current work showed and output result of 90 % accuracy.

***Keywords*:** Convolutional neural networks; mobilenet; keras; machine learning; deep learning, image classification tensor flow; python; skin cancer

ÖZET

Cilt kanseri günümüzde tüm dünyada büyük bir sorundur ve teknoloji çağından dolayı sorunu insan yerine makinelerle çözmek önemlidir. Derin öğrenme cilt kanseri problemlerini çözmenin en iyi yollarından biridir. Derin öğrenme, büyük veri, sanal gerçeklik ve artırılmış gerçeklik ile mikro hizmetleri kullanan modern teknoloji içinde yeni bir araştırma alanıdır. Muazzam hesaplama kapasitesinin gelişmesi nedeniyle, Mobilenet (CNN) kullanan derin öğrenme uygulaması gibi teknolojiler, görüntü sınıflandırmada devrim yarattı. Derin öğrenme, farklı cilt kanseri türlerini sınıflandırmak için kullanılabilir. Bu öğrenme tekniği Mobilenet CNN algoritmaları gibi farklı algoritmalar kullanır. Macilenet algoritmaları girdideki görüntüleri tanımanın uygun yoludur ve doğru sonuçlar verir. Bu güncel çalışmada Mobilenet CNN, cilt hastalıkları tiplerini girdilerimize göre sınıflandırmak için veri setimizde kullanılmaktadır. Çalışma, kanser hastalıkları alanındaki Derin öğrenmenin uygulanmasının, cilt kanseri görüntülerini sınıflandırmanın ve tanımanın en uygun yolu olabileceğini gösterdi; bu, erken teşhis için tıp alanında çok faydalı olabilecek ve doğru teşhis sonucunu iyileştirebilir. Bu mevcut çalışma gösterdi ve% 90 doğruluk çıktı çıktı.

Anahtar Sözcükler: Evrişimsel sinir ağları; mobilenet; keras, makine öğrenmesi; derin öğrenme; görüntü sınıflandırma tensor flow; python; cilt kanseri

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LIST OF ABBREVIATIONS

CNN: Convolutional Neural Network

RGB: Red-Green-Blue

ML: Machine Learning

DP: Deep Learning

AI: Artificial Intelligence

GEMM: General Matrix Multiplies

NV: Melanocytic Vevi

MEL: Melanoma

BKL: Benign Keratosis

BCC: Basal Cell Carcinoma

AKIEC: Actinic Keratoses

VASC: Vascular

DF: Dermatofibroma

CHAPTER 1
INTRODUCTION

1.1 Motivations

Deep learning or convolutional neural networks is a form of modern technology that is developed by researchers in the area of machine learning. The main focus of machine learning is to provide algorithms that can be trained to perform a task. In recent years, machine learning can be used to automate various different processes such as image recognition, text generation, detection, and so forth. Nowadays, more robust recognition rates can be ensured by innovative machine learning techniques like deep learning. Deep learning is a machine learning area that enables computers to be trained and learned through architectures such as Convolutional Neural Networks (CNN). A deep learning is skilled at learning fast from images in a fast way in a way that it learns the patterns, colours, etc and continues to teach itself from what it has learned to improve its performance. MobileNet is a type of CNN that is recently developed for mobile and embedded vision applications (Howard et al, 2017). Mobilenet has shown to perform better than CNN in terms of computational complexity and accuracy.

Neural network (Sharma, 2018) has become a modern narrative for the public and the developers as well. However the complexity of neural networks has led to the development of a convolutional neural network CNN which has shown how useful it can be for public in their daily life. On the other hand, programming platforms have been developed to support deep learning and keras python and open source libraries such as TensorFlow (Hope, 2017). For instances are widely used which makes machine learning applications (Müller, 2016) makes it easier to build. Anaconda, Hydrogen lab and JupyterLab which are examples of IDEs have enabled easier implementation of machine learning techniques. Advanced neural network architectures have advanced rapidly to encourage the use of machine learning.

1.2 The Importance of Deep Learning for Skin Cancer Classification

Nowadays the role of machines is very important in medical field. In medical field such as classifying skin cancer diseases. Deep learning using skin cancer images can ease the diagnosis of doctors among different skin cancer types. Doctors just take a picture of the patient and pass through to a deep learning architecture (such as MobileNet) in order to tell or help the doctor to diagnose the skin cancer type. That is why deep learning can ease the diagnosis without lab tests or extra cost. However, a robust and accurate learning model is vital. MobileNet is an architecture that is better suited to mobile and embedded vision applications where computing power is lacking. The major difference between the MobileNet architecture and a traditional CNN is instead of a single 3x3 convolution layer followed by batch norm and ReLU, MobileNets split the convolution into a 3x3 depthwise conv and a 1x1 pointwise conv. The importance of MobileNets are based on a streamlined architecture that creates light weight deep neural networks using deeply separable convolutions.

1.3 Objective

The main objective of this research using deep learning in order to correctly classify skin cancer types, our main objectives can be summarized as follows:

- To study different skin cancer types.
- To study and analyse the theory of machine learning.
- To find/create a dataset for skin cancer classification using existing dataset.
- To study and develop a deep learning model in order to correctly classify different skin cancer types.

1.4 Significance of Research

The existing works of CNN for skin cancer classification mostly have 80% to 90 % classification accuracy but our results are better than the previous work. Anaccuracy of up to 97% can be achieved.

CHAPTER 2

LITERATURE REVIEW

In this chapter first skin cancer types are discussed. Then, an explanation of the related work for skin cancer classification using deep learning is given.

2.1 Integumentary System of skin cancer

The skin is the body's largest organ and consists of two layers — the epidermis (the outer layer) and the dermis (the inner layer). The epidermis is a meager layer of cells and over the inner dermis forms a defensive layer. It acts to prevent ailments on the inner layers of the skin. Melanocytes (skin cells) contain melanin that assimilates light vitality and protects against the harmful effects of the sun's bright rays.Melaninprovides the skin with a form of shade.

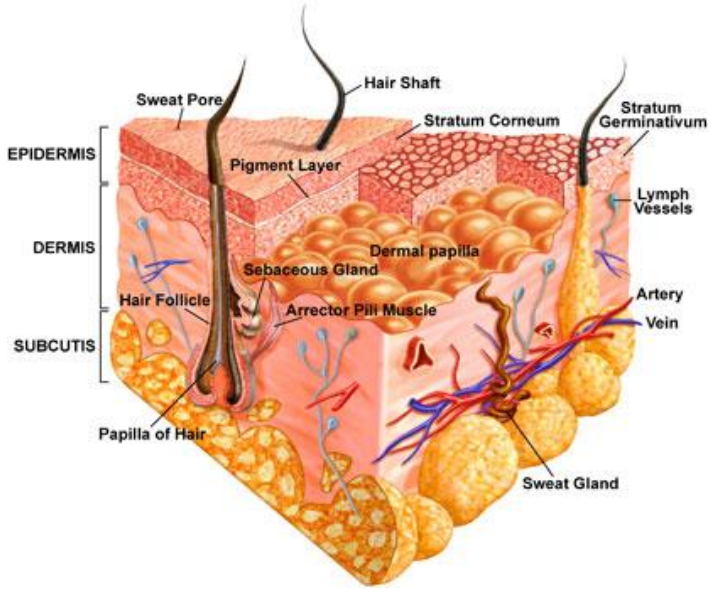


Figure 2.1: Integumentary System of skin cancer

2.2 Skin cancer

Skin cancer is the unrestrained irregular growing in skin cells. It happened when unrepaired DNA injury to skin cells, (most of the time produced by electromagnetic energy from sunshine or tannings beds) activity changes, or inherited faults. As a result the top of the skin cells grow fast and procedure malignant tumours. Here are 2 main kinds of skin cancer, melanoma and non-melanoma. These are explained in details below

Melanoma is a type of skin cancer that begins in your skin's pigment control cells (melanocytes).This illustration shows melanoma cells that extend to the deeper layers of the skin from the surface of the skin.

Non-melanoma skin cancer refers to a group of cancers in the upper layers of the skin that grow slowly.

The incident rate of skin cancer continues to increase for melanoma and non-melanoma skin cancer; 5.4 million new cases of squamous cell carcinomas have been reported in the U.S each year (Linos et al.,2017).

The number of melanoma deaths is predictable to decrease by 22% in 2019(Zengul et al.,2019).

2.2.1 Melanoma

This is the event of uncontrolled organic process of melanocytes that eventually opened up into the encircling layers of the skin. In the United Kingdom11,000 people are diagnosed with skin cancer each year round the ages of 15-34 years (Walters-Davies, 2013). There are four types of skin melanoma, the nodular melanoma, superficial spreading melanoma, acral melanoma and nodular lentigomaligna melanoma. The lentigomaligna skin cancer principally affects older people on the portions of the skin that are over visible to the sun over the years, the acral skin cancer is seen on the feet or palms of the hands and has be determined to be gift in afro Caribbean origin. The risk factors related to skin cancer are; skin sort, reduced immunity and genetic science. There are four stages of melanoma stage 1, 2, 3 and 4.

2.2.2 Melanocytic Nevi

Melanocytes are cells that create colors on the skin and normally live within the epidermis, in the dermo-epidermal intersection, and in the follicles of the hair. Some benign neoplasm's are derived from melanocytes and are the consequence of individual oncogenic transformations on a regular basis (Damsky et al.,2017).There are three kinds of melanocytic nevi; inherent melanocytic nevi and other nevi acquired (Sardana et al., 2014).Routine melanocytic sores evaluation, is constantly examined with the decision as to whether an injury is benevolent or threatening (Sardana et al., 2014).There is currently no overall consensus on which criteria should be included in this activity. Melanocytic nevi are much encircled, round to ovoid, with periphery defined by normal and all around. Although most are clinically analyzed, another characterization framework for nevi was suggested in 2007, taking into account dermo-scopic highlights.

2.2.3 Acquired Melanocytic Nevi

Normal acquired melanocytic nevi (CAMN) are a typical disease, which is largely procured, due to the kind of nevus cell multiplication. This skin disease, also mentioned to as "signature nevi, has been variably classified depending on the anatomic, architectural, and cellular histological pattern. Melanocytic nevi form a convenient head to classify the varied manifestations of both congenital and acquired nevi, of which our focus is largely on the common acquired nevi.

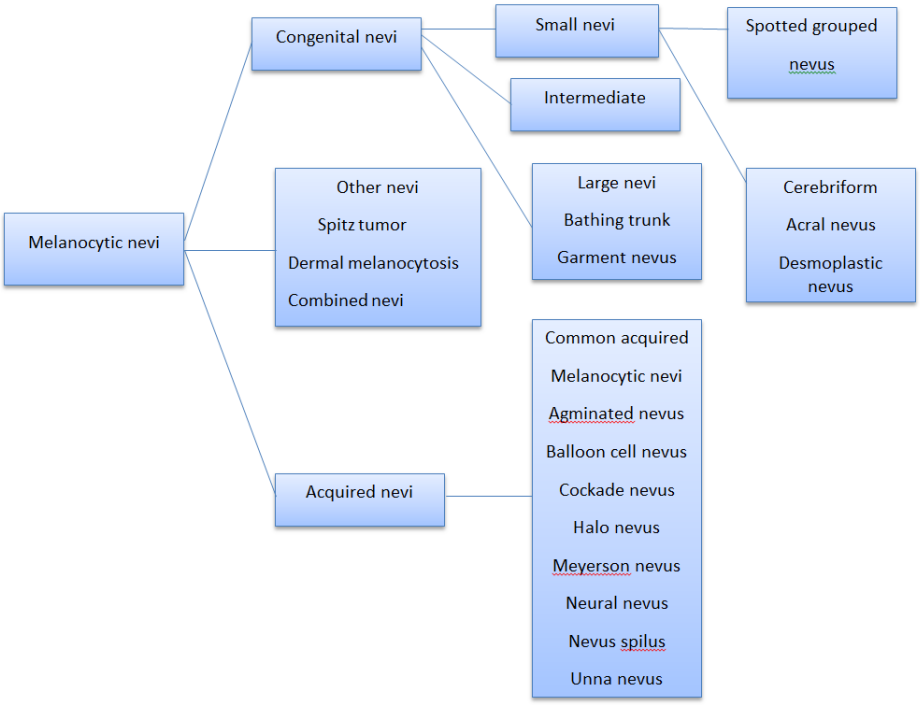
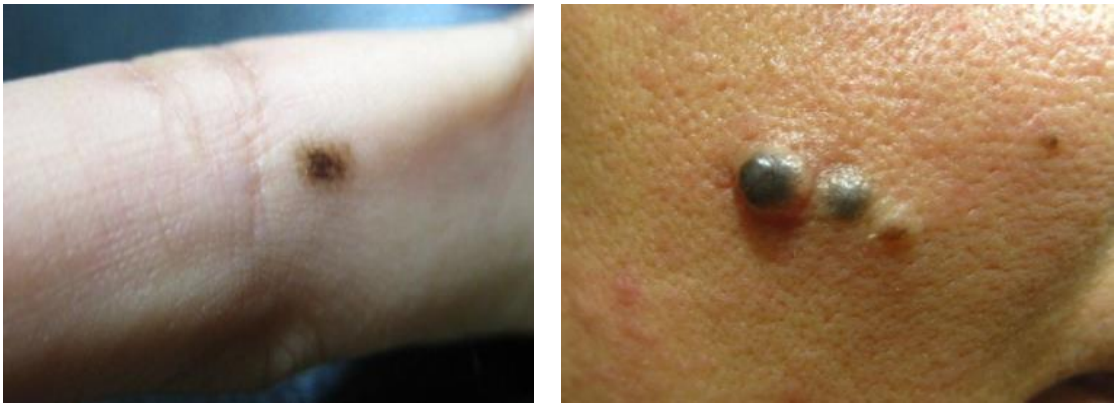


Figure 2.2: Clinical classification of common acquired melanocytic nevi



(a) **(b)**

Figure 2.3: examples of common acquired melanocytic nevi on the a and b. face

In the treatment of melanocytic nevi, the clinician should make sure that melanoma or dysplasia is likely. Dermoscopy, biopsy and more rapid and less harmful "strategies studied were described in the therapy and conclusion of a distinctive nevi (biopsy and

shave, punch,). Most fundamental therapy finished; are laser expulsion by CAMN is itself disputable since there are no examples' presented for tissue analysis and edge evaluation.

2.2.4 Congenital Melanocytic Nevi (CMN)

Congenital melanocytic nevi (CMN) can be light darker to dark patches or plaques, can exhibit in factor ways, and spread almost any size surface territory or any piece of the body. The rate of CMN is by all accounts free of skin shading or other ethnic components. Little to medium CMN is anticipated to happen in more than one out of a hundred births.

2.3 Non-melanoma Skin Cancer

Non-melanoma skin cancer refers to all kinds of skin cancer not melanoma that occur in the skin. The broader category of non-melanoma skin cancer includes several types of skin cancer; they are divided in different types.

2.3.1 Basal cell carcinoma (BCC)

BCC is a danger to the epidermis ' basal cells. It is vital in the United Kingdom and documents 75%of all non-melanoma skin threatening developments. Fortunately, BCCs are generating moderately and never metastasize (<0.1%). More commonly, BCCs occur on sun-revealed skin domains, such as the face and scalp, and are generally held to hair-bearing skin.

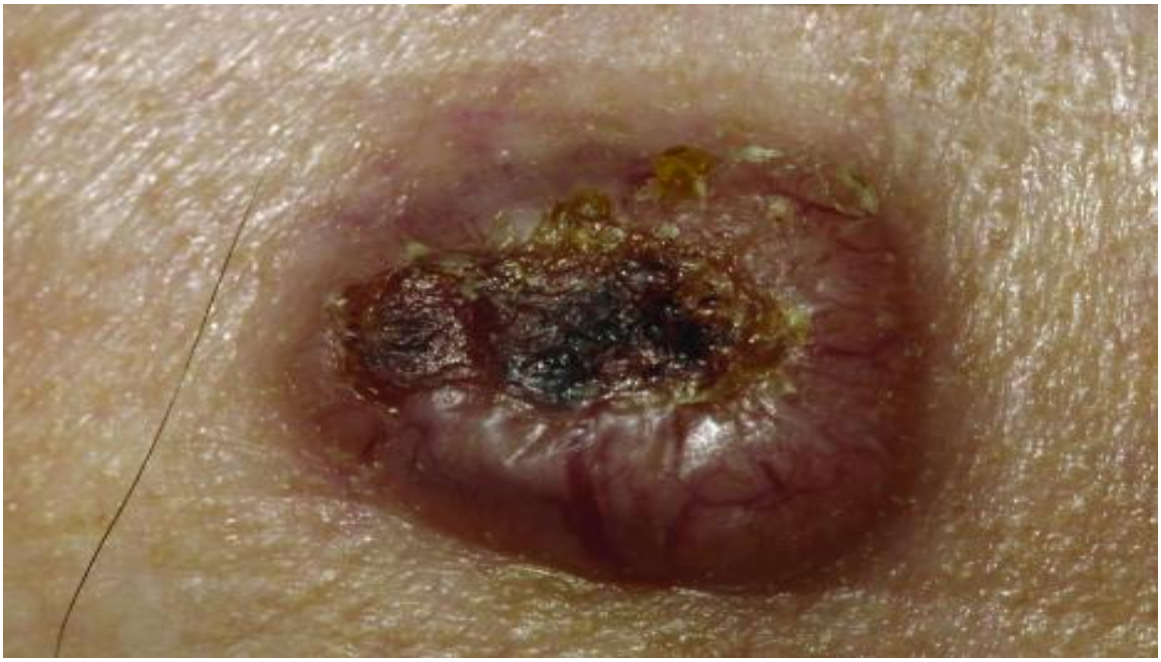


Figure 2.4: Basal carcinoma on forehead

2.3.2 Squamous-cell carcinoma

This type of carcinoma is a dangerous development of keratinocytes on the epidermis which makes about 20% of non-melanoma skin cancers, Squamous cell carcinomas appear on domains of the skin exposed to the sun. This carcinoma appears as a red swelling or sometimes a non- recovering damage, which can cause depletion and ulceration. They are normally incredible treatment for this regardless about 5-10% often metastasise at the starting time after affecting the lymph center points.

Other hazardous elements are associated with previous skin malignancies, previous radiotherapy.

2.3.3 Actinic Keratosis

There are no clear recommendations yet about the treatment of actinic keratosis even though it is one of the most frequent premalignant skin disease existing among the white population (jansen et al., 2019).

Actinic keratosis is caused by exposure to UV radiation and has a prevalence rate of 37.5% in the white population within the ages of 50years or older (Jansen, et al., 2019). Untreated actinic keratosis develops into squamous cell carcinoma (Jansen, et al., 2019). The existing

problems with actinic keratosis is the fact that there are no definitive clinical characteristics that can differentiate which actinic keratosis can be regarded as risky and to what extent the actinic keratosis would progress into a carcinoma. The treatments that exist are cryotherapy, drugs like fluorouracil however recurrence rates are high and some of the treatments can have prophylactic effects on the development of new lesions.

2.3.4 Dermatofibroma

Dermatofibroma is a commonly occurring skin component that is typically concentrated within the dermis of the skin.Dermatofibromesare referred to as the skin's kind stringy histiocytomas. Clinically, these dermis mesenchymal cell wounds are strong subcutaneous knobs that occur at the furthest points in by far the majority of instances and may be associated with overlying changes in the skin.Clinically, these dermis mesenchymal cell wounds are strong subcutaneous knobs that occur at the furthest points in by far the majority of instances and may be associated with overlying changes in the skin.

The treatment ofDermatofibromas is benign lesions with an excellent prognosis that are usually cured through surgical excision. In excisional biopsies with cellular or atypical variants, re-excision may be recommended to ensure clear margins because of the documented, albeit low, the rate of local recurrence.

2.3.5 Vascular lesions

Acquired vascular lesions are common skin findings. They appear “vascular,” or filled with blood. Acquired vascular lesions differ from congenital or hereditary vascular lesions in that they manifest months to years after birth. Vascular skin sores are exceptionally normal, happening in about 40% of all kids.

2.3.6 Karposi sarcoma (KS)

It is a second-rate vascular sore of hazardous potential that introduces skin sores most of the moment. Most histopathologists are up-to-date with the histological image of prevalent (ordinary) skin KS as it progresses from fixation to plaque. This morphological variety of "periodic" KS is fundamental to large, endemic African, transplant-related and AIDS-related KS (Grayson, et al., 2008).

2.3.7 Merkel cell carcinoma (MC)

MC affects the head, neck or individuals and appears with a sparkly surface as red or purple levers. Merkel cell carcinomas are preferred for adjacent repeat and adjacent or removed metastasis. Merkel cells are discovered in the skin's top layer and near endings of the nerves.

2.3.8 Cutaneous white platelet lymphoma

Cutaneous white platelet lymphoma is a type of lymphoma that is not Hodgkin's. Bargaining Microorganisms of the immune system migrate to the skin and cause structure injuries that alter shape as developments in sullying. For example, sarcomas start from mesenchymal cells, bone and fragile tissue (skin tallying).

2.4 Related Work for Skin Cancer Classification Using Deep Learning

Recognizing melanoma, non-melanoma and various types of skin wounds is an important filed, and recently different CNN based methods are proposed.

(Sasikala et al., 2018) propose one of the most popular articles that uses CNN for the recognition and classification of malignant growth. They state that the accuracy of their proposed CNN is more efficient than most of the neural systems. Thus CNN can be a good alternative for classification malignancy grouping andthe accuracy of the CNN method is 96% but the dataset for this scheme was reasonably small 1000 images.

(Pomponiu et al., 2016) use only 399 images to arrange melanomas versus nevus typed.In this study that use a pertained deep neural network (DNN). Once again, this dataset is unreasonably small for a scheme that should characterize such sensitive client data. This method achieves 92.1 % affectability, 95.18 %explicitness, and 93.64 % accuracy.

(Codella et al., 2015) use 2624 Universal Skin Imaging Coordinated Effort (ISIC) dermatoscopic images. They apply transfer karnmy using AlexNet; in addition they apply scanty coding, deep leftover scheme, and convolutionary U-organization. After extraction factures using transfer learning a support vector machine is used for classification. They achieve 93.1% accuracy, 94.9% affectability, and 92.8% peculiarity for grouping melanoma versus non melanoma. An accuracy of 73.9 percent, an affectability of 73.8

percent, and an explicitness of 74.3 percent were accounted for more troublesome segregation between melanomas and atypical nevi.

(Kawahara et al, 2016) utilize a multi-class classifier with 10 labels using AlexNet (transfer learning) extract features. The creators used 1300 images of 10 skin lesions and announced 81.8% accuracy.

(Brinker et al., 2019) use in-depth information on how to prepare CNN with 12,378 open-source dermoscopic images and used 100 images to evaluate the performance of CNN with 157 dermatologists from 12 different college emergency hospitals in Germany. The standard affectability and Particularity performed by dermatologists with dermoscopic images (which were the evaluation measurements used in their journal) was territory74.1%and 91.3 %.

(Hosny et al., 2019) study skin injury techniques (melanoma and so on) using a pre-prepared CNN model using transfer learning with AlexNet. They use ph2 dataset and the accuracy is accuracy (98.61%), affectability (98.93%), explicitness (98.93%)and accuracy (97.73%).

(Mendes et al., 2018) examine the significance of programmed characterization technique to help skin sores conclusion utilizing CNN. The scheme was tested with 956 clinical images and accomplishes a territory of 96% for Melanoma under the Area under the Curve (AUC) and 91% for Basal Cell Carcinoma.

(Ramlakhan et al., 2011) introduce a prototype of an automated image-based melanoma identification scheme for Android smartphones. The scheme comprises of three main parts: segmentation of images, calculation of features and classification. A skin lesion image is converted to a monochrome image for outline contour detection. They are used as an input KNN for classifier; in that work just two classes used melanoma and convenient automated diagnosis of skin. They achieve an average precision of 66.7%, with an average recall / sensitivity of malignant class of 60.7% and a specificity of 80.5%.

(Ruiz et al., 2011) present a clinical decision support scheme for diagnosing melanoma using in pictures set of the skin lesion to be diagnosed as input. In order to extract the impacted region, the scheme analyses the picture sequence, determines the features that show the degree of harm and it makes a choice according to them; they are used as an input

KNN for classifier, a multilayered perceptron, a Bayesian classifier and the K- Nearest Neighbour (K-NN) algorithm. They are achieves approximately 87% and accuracy are 73.47%, 80.6% and 86.73%.

In the research of (Harangi et al., 2018), a set of state-of-the-art deep learning methods are used to identify disease. The ensemble submitted consists of the CNNs AlexNet, VGGNet, GoogLeNet, they have won the most prominent ImageNet challenge in the world to classify images in the years to come. They are used three classes and the accuracy of this research are 79.3%, 79.9%, 81.2% and 80.7%.

(Esteva et al., 2017) classify skin lesions using a single CNN is demonstrated, trained end-to-end straight from pictures, using as inputs only pixels and disease labels. They compared of 2,032 different skin cancer cases. They testing its performance against 21 board certified dermatologists on clinical biopsy proven pictures with two critical instances of binary classification: Carcinomas of keratinocytes versus benign seborrheickeratoses; and melanomas versus benign nevi and The accuracy of 69.4% and 72.1%.

The efficacy and capacity of convolution neural networks is studied by (Rogers et al., 2018). They are used Melanoma, melanocytic nevi, basal cell carcinoma, keratosis benign, actinic keratosis and carcinoma intraepithelial. The goal is to compare deep learning skills with extremely qualified dermatologists ' results. For melanoma and basal cell carcinoma, the highest ROC AUC values are 94.40%, 82.26% and 88.82% respectively of dermatologists.

(Mahbod et al., 2019) recommend a fully automatic computerised method to classify skin lesions from Dermoscopic images. Their approach is created on a novel ensemble scheme for CNNs that combine intra architecture. The recommended method consists of multiple sets of CNNs of different architectures that represent different feature abstraction levels; they used on the 600 test images of the ISIC 2017, the accuracy of melanoma is 87.3% and seboeeheic keratos is 95.5%

In the work of (Bi et al., 2017), ISIC 1600 images and 150 epochs are used. They fine-tuned the CNNs model, in the last layer are modified with ResNet, the numbers of the classes is 3and they achieve the accuracy 96.90%, 97.00% and 97.60%.

2.5 Summary of results of the current research and related works

To summarize, CNN is stored to be extensively applied for skin cancer and skin wounds classification. However, there are lacks of existing datasets; some methods use a small size of samples, there are few clinical image datasets and generally each method creates a new dataset for their purpose. On the other hand, many CNN methods apply transfer learning such as AlexNet features are utilized. In this work, a CNN network is trained using MobileNet which has a large collection of multi-source dermoscopy images to test and train; as compared to previously proposed models the MobileNet model has shown accurate and reliable performance in addition to its faster performance, and lightweight architecture. Network size reduced when the images are increased to the network size the MobileNet accuracy is increase; it is used in mobile as application. In addition, an image dataset is created form GitHub number of skin cancer images that are used in the dataset are 64,000. Result show that we can achieve an accuracy of 97%, which is very competitive comparing to the state-of-the-art methods.

CHAPTER 3

CONVOLUTIONAL NEURAL NETWORKS

In this chapter, the concepts of artificial intelligence, machine learning and deep learning are discussed. In particular, MobileNet is explained which is a part of CNN that is used in this thesis.

3.1 Artificial Intelligence (AI)

AI is a field of software engineering which was began with the start of software engineering history. Alan Turing, in 1950 (Turing and Yang, 2013), author of software engineering, posed the inquiry "Can machines think?" which set the absolute first achievement for AI considers. Later Arthur Samuel characterized AI as "field of concentrate that enables PCs to learn without being unequivocally customized". Be that as it may, AI was at long last characterized by Tom M. Mitchell: "A PC program is said to gain as a matter of fact E regarding some class of errands T and execution measure P, if its exhibition at assignments in T, as estimated by P, improves with the experience E."

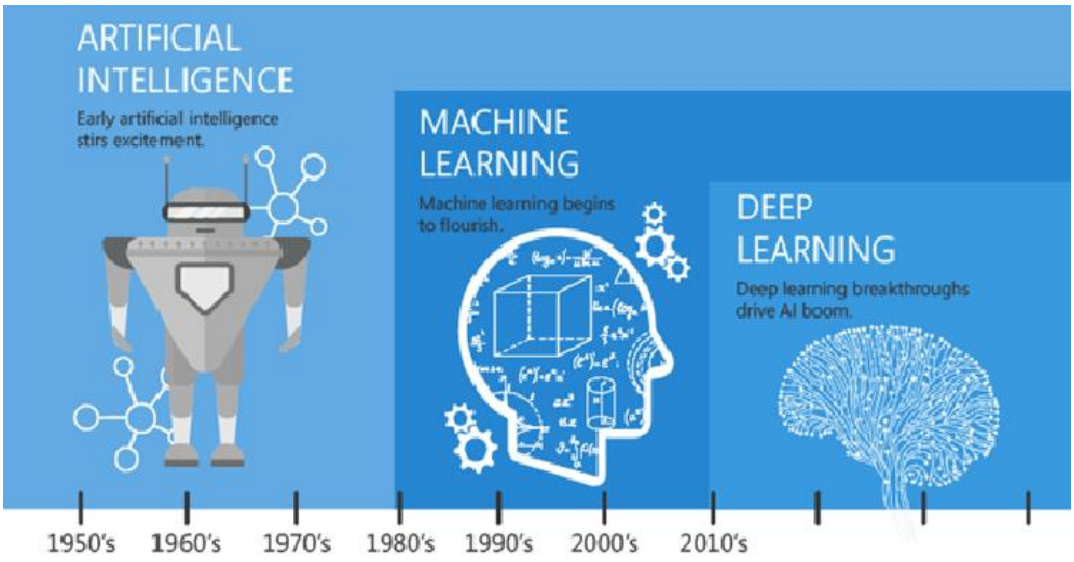


Figure 3.1: Machine Learning, Artificial Intelligence and Deep Learning connections

Convolutional Neural Networks (CNN) or known as deep learning is a part of machine learning, and that machine learning is a part of artificial intelligence (AI). Figure 3.1 (Organization of Electrical and Gadgets Architects, 2013) summarizes the relationships between deep learning, machine learning and AI. It is seen that AI is here since 1950, where machine learning is the subset of AI or a piece of man-made consciousness which started to thrive since 1980. On the other hand, deep learning is also a subset of AI, which was appeared in 2010. Deep learning is a relatively new topic but it has changed the way man-made consciousness works; CNNs literally can be applied to any data such as text, speech, images and achieves outstanding results.

3.2 Machine learning (ML)

Machine Learning (ML) is a subset of man-made brainpower which spotlights for the most part on AI from their experience and making forecasts depending on this experience.ML is the scientific study of algorithms and statistical models used for the computer systems to perform a particular task without using specific directions, relying instead on patterns and inferences. It is seen as an artificial intelligence subset. ML algorithms create a sample based mathematical model. Identified as training data to create predictions or decisions without specific programming to achieve the task.

AI calculation is prepared utilizing a preparation informational collection to make a model. At the point when new information is acquainted with a ML calculation, it makes a forecast based on the model. Figure 3.2 explains the workflow of a machine learning application.ML starts with reading and observing the training data, to discover useful insight and patterns to make a model that predicts the right outcome. The efficiency of the model is than assessed using the test information set. This method is carried out up until; the machine learns and maps the input to the correct output automatically without any action by humans.

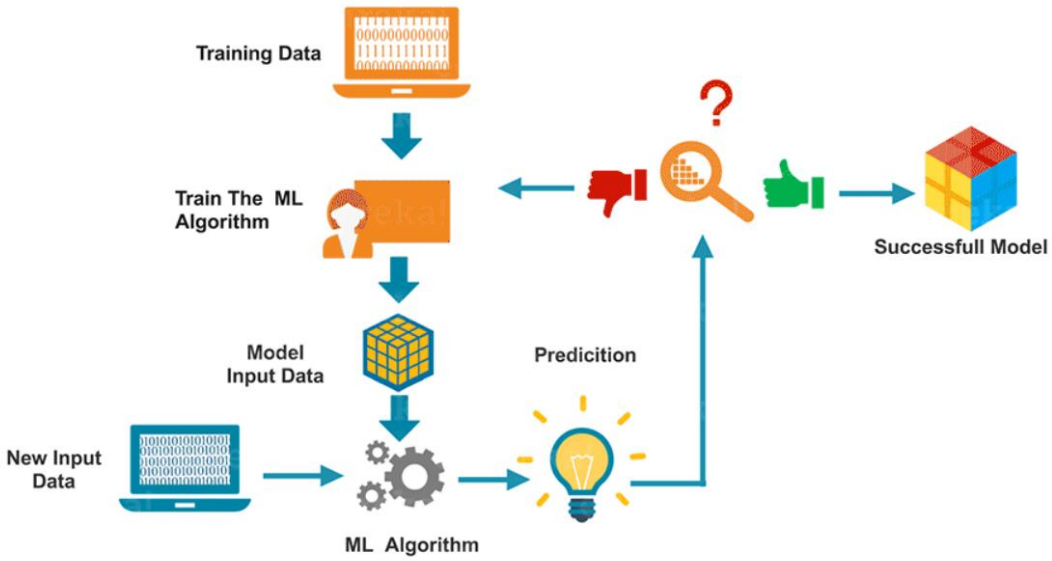


Figure 3.2: How Machine learning works

3.3 Types of Machine Learning

Machine learning can be further subdivided into various types. The four most important types of machine learning have been given below, namely supervised machine learning, unsupervised machine learning, and reinforcement and semi supervised learning

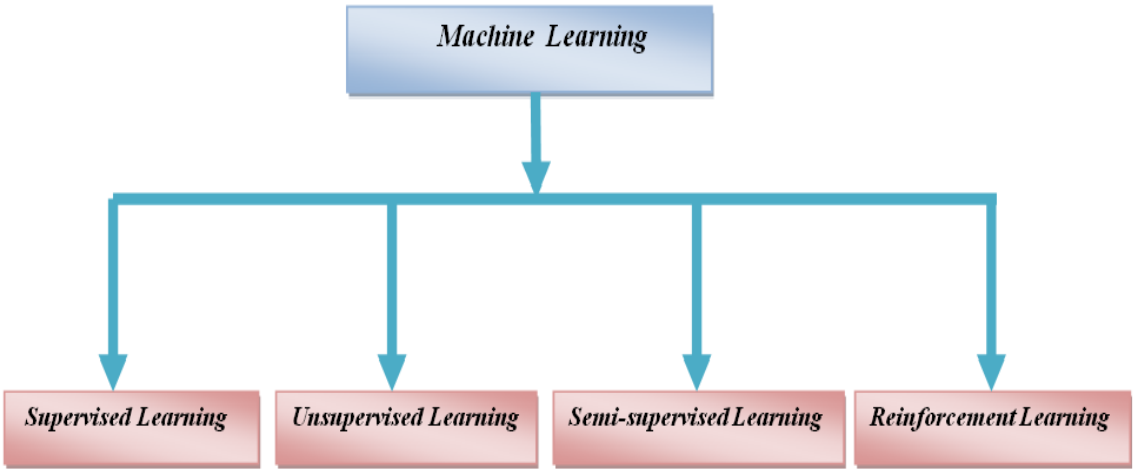


Figure 3.3: Machine learning types

3.3.1 Supervised Learning

In supervised learning, the dataset is the collection of labelled, where input variables (x), output variables (y) and learn the mapping function from input to output to use an algorithm. $f(x) = y$

The aim is to approximate the mapping function so well that you can predict the output variables (y) for that data when you have new input data (x) or our goal, given a training set, is to describe the supervised learning problem slightly more formally, to study a feature h: x → y so that h(x) is a good analyst for the corresponding value of y. this feature his called a hypothesis. It is shown practically below like this.

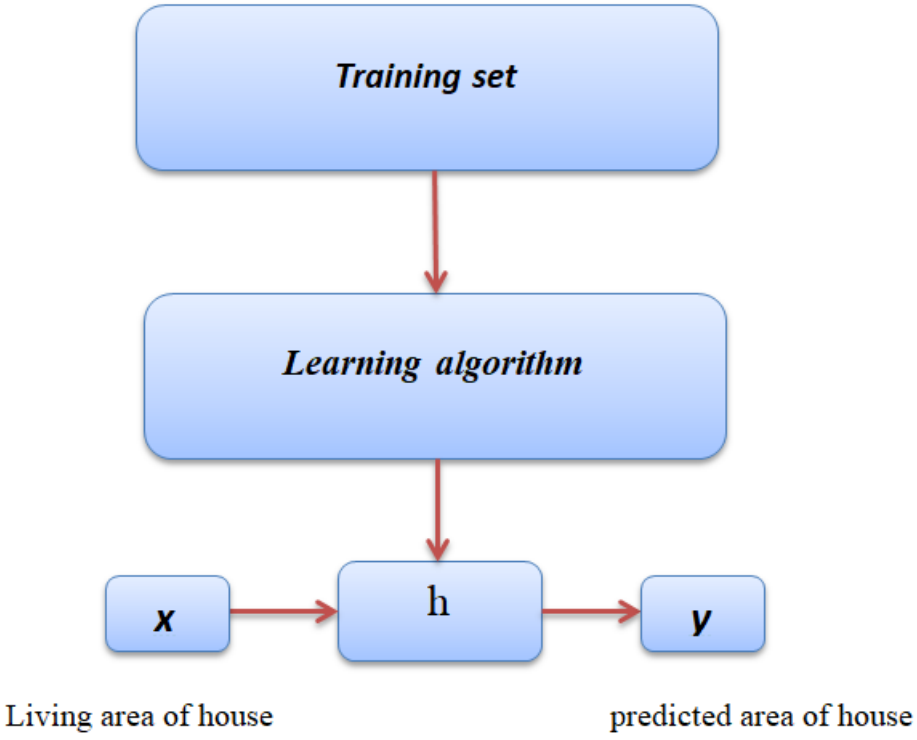


Figure 3.4: Mapping function of supervised learning

When trying to predict the target variable is continuous, like in a housing instance, it is called the problem of learning a regression. If y can only take on a small of discrete values

such as given the living area, to be predicted if a building is say, a house an apartment, it can be called a problem of classification.

Supervised learning challenges can also divide by regression and classification. A classification problem is when a category such as ‘red’ or ‘blue’ or ‘disease’ and ‘no disease’ is the output variable. A regression issue is when a real value like ‘lira’ or ‘weight’ is the output variable.

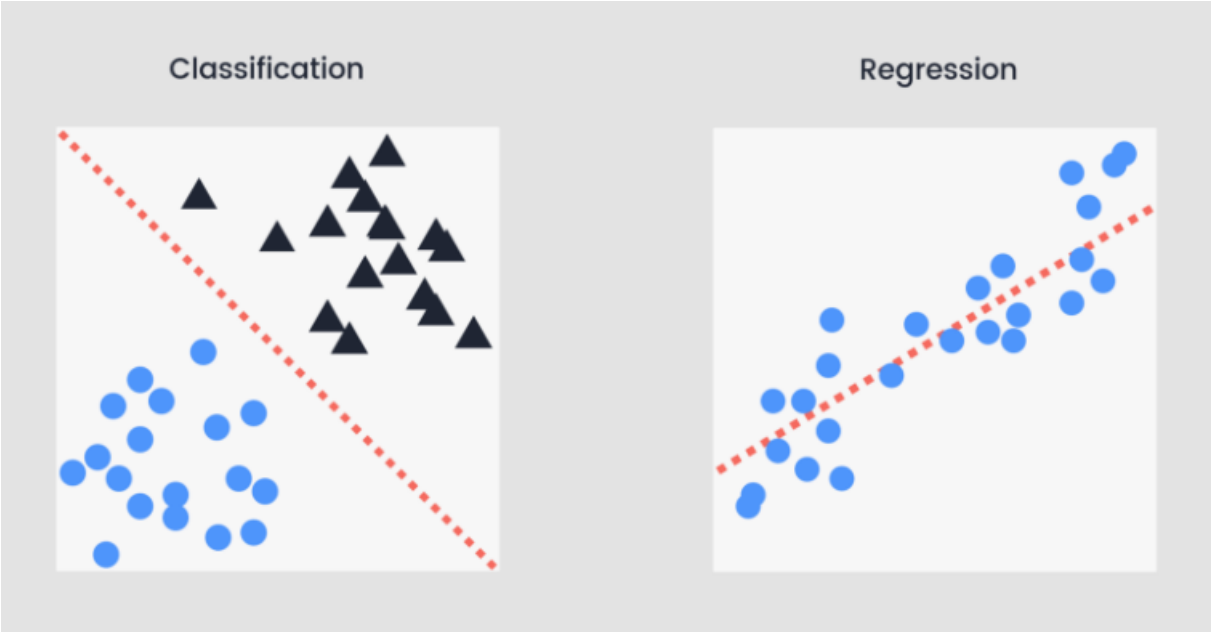


Figure 3.5: classification and regression

3.3.2 Unsupervised Learning

The second sort of machine learning is unsupervised learning. In this kind of machine learning, results are unmistakably classified with conceptual conditions and non-marked or supervised learning is the region there are no dependent variable

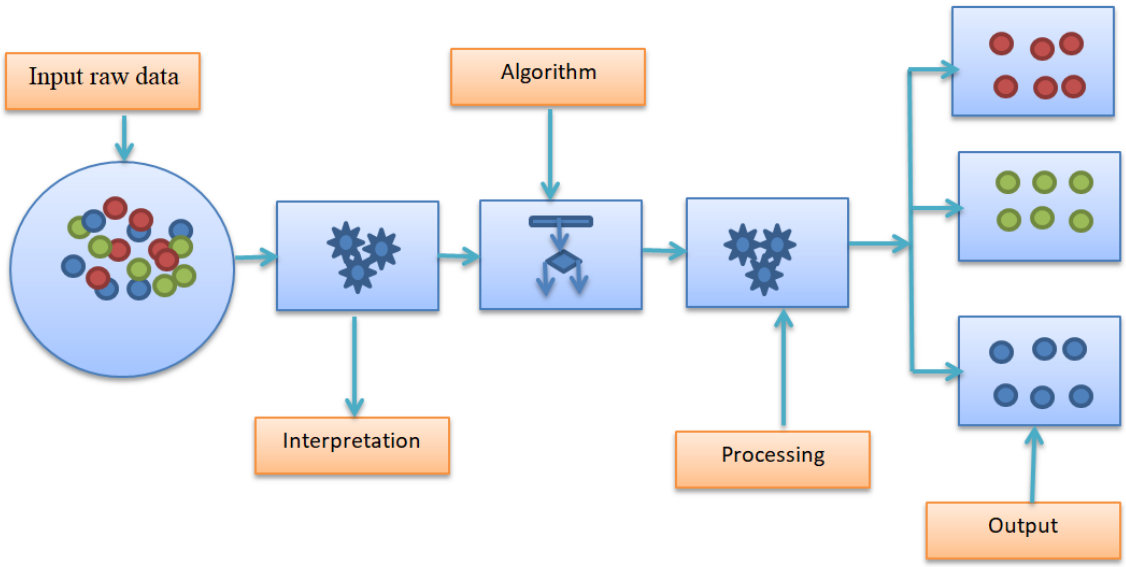


Figure 3.6: Workflow of unsupervised learning

In this method the first thing is to start with the points as individual clusters as it travel forward, in every step, in Marge the nearest cluster pair there is only one cluster reaming. In that system three types unknown data without labels, the system does not have specific information set during the unsupervised learning and the outcomes the most of the difficulties are largely unidentified. In easy term, when goes the operation, the AI system and ML objective are blinded, the system has immense and faultless logical operation to guide it along the way, but the availability of adequate algorithms for input and output makes the system even more complicated. Amazing as the full system sound, unsupervised learning is able to interpret and finding a solution to an unlimited number of data, through input data and the mechanism of binary logic current in all computer systems. The model does not have any reference data.

3.3.3 Reinforcement Machine Learning

Reinforcement learning is a field of machine learning. In a specific situation, it is about taking right action to maximize reward. Different software and machines use it to learn the best behaviour or route it should take in a specific scenario. Reinforcement learning differs from supervised learning in such a way the training data have the main answer in

supervised learning so that the model is trained with the right response itself while reinforcement learning. There is no answer but the reinforcement agent chooses what to do to achieve the give task. Without the training dataset, it is sure to learn from its experience. There are five components is connected with reinforcement learning.

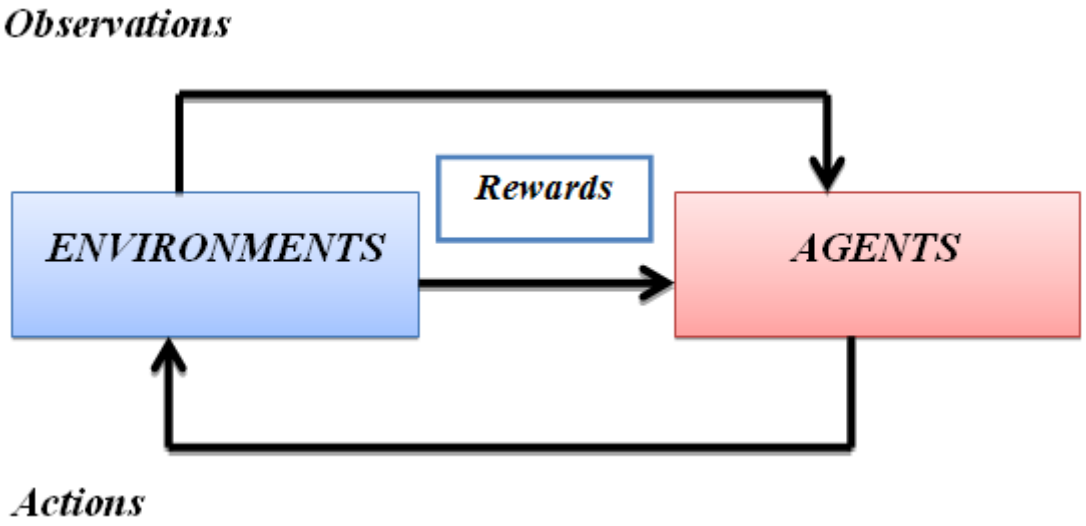


Figure 3.7: Workflow of Reinforcement Machine Learning

The agent is an intelligent program that is the initial section and decision maker in the reinforcement learning. The surrounding region is the environment that has the agent's goal to perform. An internal condition is maintained by an agent to study the environment. Actions that are the tasks performed in the environment by the agent, rewards that are used to train agents (Krittanawong et al., 2017).

3.3.4 Semi supervised learning

Semi Supervised learning is a learning model concerned with studying how machines and natural systems like humans learn when ladled and unlabelled information are clearly present. Either learning has traditionally been studied in the unsupervised paradigm (e.g. outlier detection, clustering) where all the information is unlabelled, the objective of semi

supervised learning is to understand how the combination of labelled and unlabelled information can change the learning, and design algorithms using such a combination.

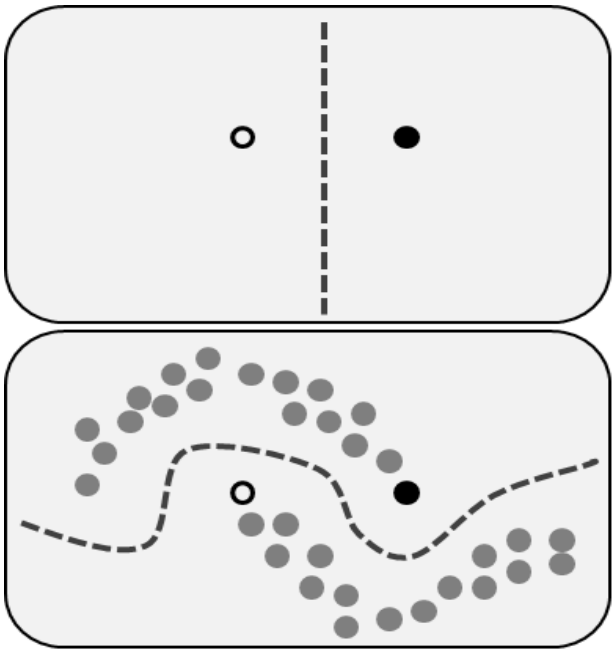


Figure 3.8: unlabeled data influence in semi-supervised learning

An example of unlabeled data influence in semi-supervised learning.The top panel shows a boundary of decisions that might be adopted after seeing only one positive white circle and one negative black circle example. The bottom panel shows a decision boundary that could be taken if a collection of unlabeled data gray circles were given in addition to the two labeled examples.This could be viewed as clustering and then labeling the clusters with the labeled data, pushing the boundary of the decision away from high-density regions (Zhuet el., 2009).

3.4 Convolutional Neural Networks (CNN)

CNN is advanced version of neural networks. There are hidden layers instead of one layer of neural network. CNN are multilayer perceptions that are regularized versions, usually multilayer perceptions refer to fully connected networks, that is the next layer connects each neurons in one layer to all neurons. This network is a full connectivity makes them expected to over fit data.

Convolution Neural Systems are not quite the same as would be expected neural systems since they contain an uncommon sort of layer called a Convolutional Layer, CNNs are consisting of convolutional layers. An initial layer generally applies edge recognition. Later on, layers can identify progressively complex features. These element maps are put into a not insignificant rundown of highlights toward the finish of the system, which is utilized to at long last arrange the image. Apart from convolutional layers, CNNs contain a couple different layers, in particular pooling and characterization layers.

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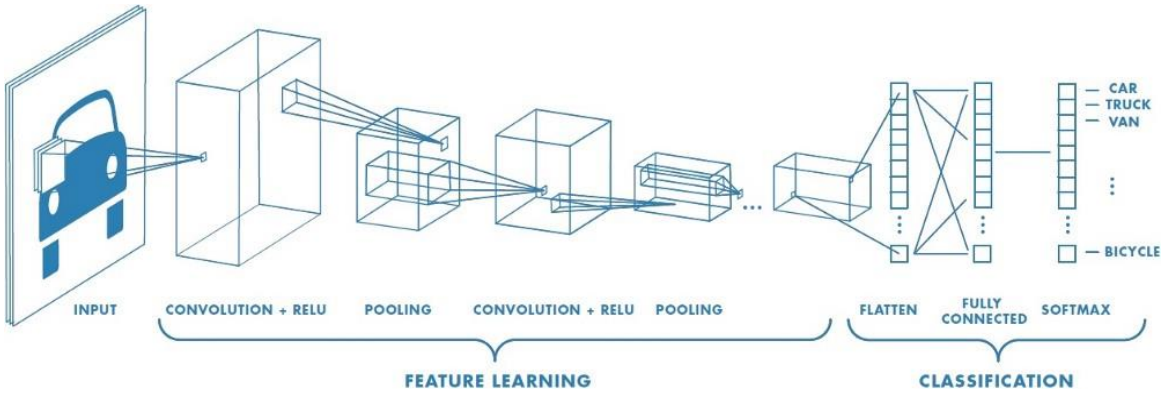

Figure 3.9: Standard architecture of a CNN

3.4.1 Convolutional layer

A convolutional layer is always the first layer in CNN. It should be having the following attributes; input is a shape image number x image width x image height x image depth. Convolutional kernels with hyper parameters in width and height, and the depth of which

must be equal to that of the image. Convolution layers convert the input and pass it to the next layer. This is similar to the visual cortex response of a neuron to a specific stimulus

$$(\boldsymbol{f} * \mathbf{g})(\mathbf{t}) \stackrel{\text{def}}{=} \int_{-\infty}^{\infty} \boldsymbol{f}(\boldsymbol{\tau})\boldsymbol{g}(\boldsymbol{t}-\boldsymbol{\tau})\,\boldsymbol{dr}$$

3.4.2 Relu layer

Relu is stand for rectified linear unit, and is an activation function type; Relu is most widely used neural network activation function, especially used in CNN. The output is

$f(x) = max(0,x)$

3.4.3 Pooling layer

Another building block of the CNN is a pooling layer. Its function is to step by step reduce the representation's spatial size to reduce the amount of parameters and the networks computation. Poling layer operates independently on each feature map. In pooling layer are different approaches in most common approach is used max pooling, Average pooling, Global average pooling and Global max pooling. These 4 approaches the first and second are used in between convolution layers, third and fourth are used at the end stage.

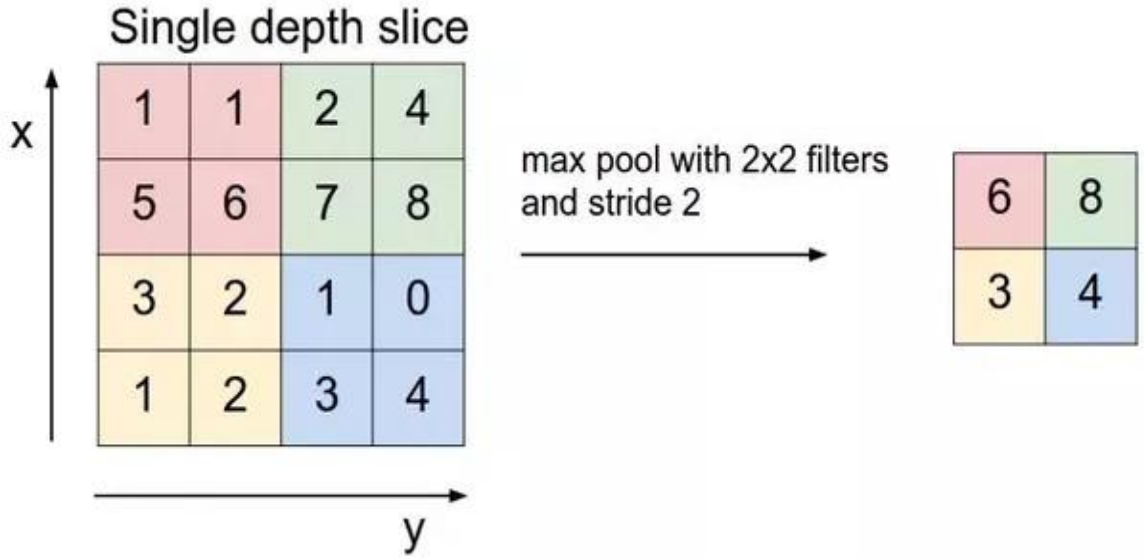

Figure 3.10: pooling layer

3.4.4 Fully connected layer (FC)

Usually the last few layers of a CNN fully connected layers. Each neuron receives input from each of the previous layer elements. The entire previous layer is the receptive field. The receptive area is smaller in a convolutional layer than the entire previous layer.

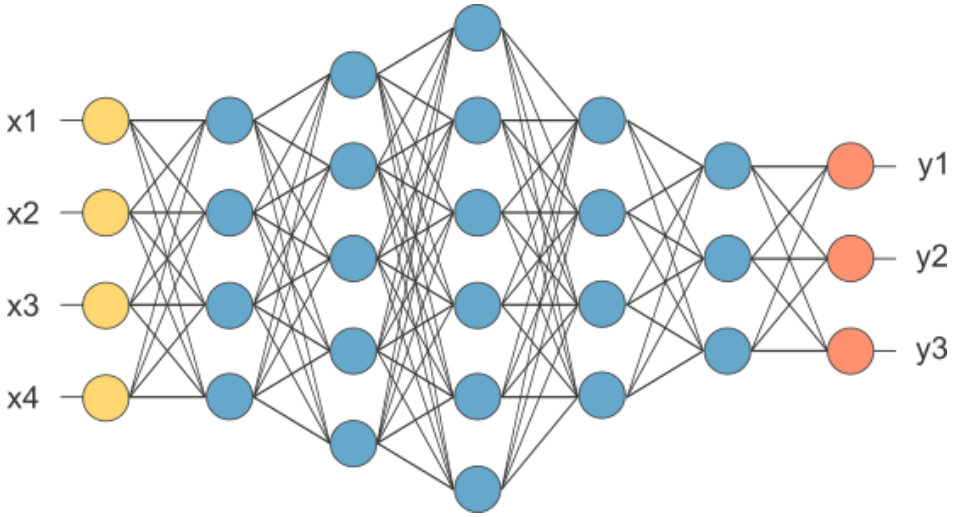

Figure 3.11: Fully connected layer

3.5 MobileNet

MobileNet is more suitable architecture for mobile and embedded version applications where the computing power is lack. In terms of training speed but also in terms of prediction in real time, MobileNet are a class of convolutional neural system planned by analysts at Google in April 2017.A few things make MobileNet awesome' insanely small, fast, remarkably accurate, easy to tune for resource with accuracy. MobileNet covers less amount of space and can be trained very quickly comparing to CNN, as well as it is simple to tune and provides more accurate classification results comparing to CNN. The image size should greater than 32x 32 pixels for MobileNet otherwise it will be false. In the work224, 224, 3 image sizes of RBG were used.

MobileNet architecture uses depthwise separable convolutions that significantly decrease the number of parameters compared to normal network convolutions with the same

network depth, the results in deep neural network with lightweight. In the common convolution is replaced by deptwise convolution followed by in point-wise convolution called as a convolution separable from the depthwise.

3.5.1 Convolutional Decomposition

MobileNet uses the idea of factorized convolution for reference and divides ordinary convolution operations into two parts: Depthwise convolution and point wise convolution.

In depthwise convolution, each convolution core filter convolutes only for a specific input channel, as shown in the following figure, where M is the number of input channels and DK is the size of the convolution core.

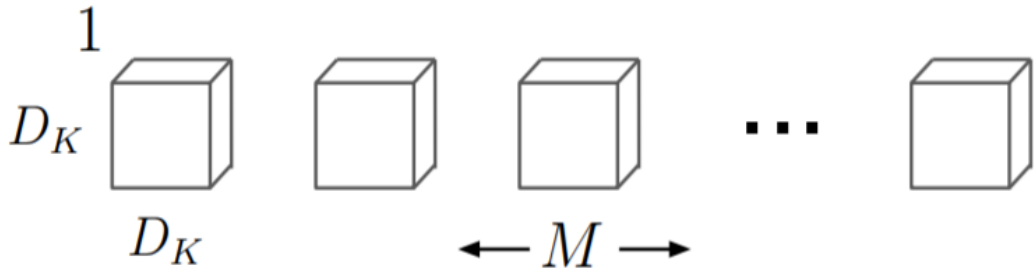

Figure 3.12: Depthwise Convolution

The computational complexity of Depthwise convolution formula is:

DK*DK*M*DF*DF

Where DF is the size of the feature map of convolution layer output:

In pointwise convolution, the multi-channel output of depthwise convolution layer is combined with a convolution core of 1×1 size. As shown below, N is the number of output

channels. For convolution cores of 3×3 size, depthwise separable convolution can theoretically increase the efficiency by about 8-9 times. The formula is:

$$\frac{Dk * Dk * M * Df * Df + M * N * Df * Df}{Dk * Dk * M * N * Df * Df} = \frac{1}{N} + \frac{1}{Dk^2}$$

A standard convolutional layer of input a DF ×DF × M feature map F. which produces a DF × DF × N feature map G where DF is the spatial width and height of a square input feature map1, where M is the number of input channels (input depth), and DG is the spatial width and height of a square output feature map and N is the number of output channel output depth.

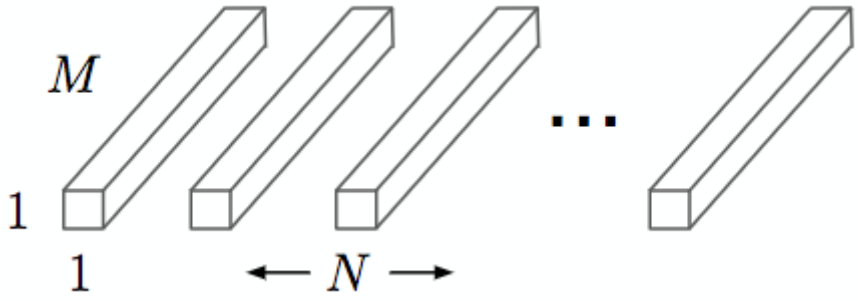

Figure 3.13: Pointwise Convolution

3.6 Comparing MobileNet and CNN Architectures

The differences between MobileNet and CNN architecture are as follows;

Low inference rate, high memory requirement to reduce complexity, high accuracy and resource friendly, MobileNet is a smaller and faster variant of CNN hence its use for image recognition.

The architecture is such that the vision models are in a collective form for Tensorflow in a mobile interface for image recognition. MobileNet uses batch normalization (BN), and

Rectified linear unit (ReLu) before it divides the convolutions into depthwise and pointwise of 3x3 and 1x1 convolution sizes respectively. The batch normalization is done to each channel in the convolution independently hence and to further reduce computational cost the ReLu or ReLu6 produces an averaged per layer output at all pointwise convolutional layers (Tao Sheng et al. 2019). ReLu reduces the quantization range and signal power (Tao Sheng et al. 2019). The Mobile net architecture changes the parameters (width and resolution multiplier) for better image\object detection computation time. The width multiplier enables thinning of the frame, while the resolution multiplier changes the data estimations of the image, diminishing the inward depiction at each layer.

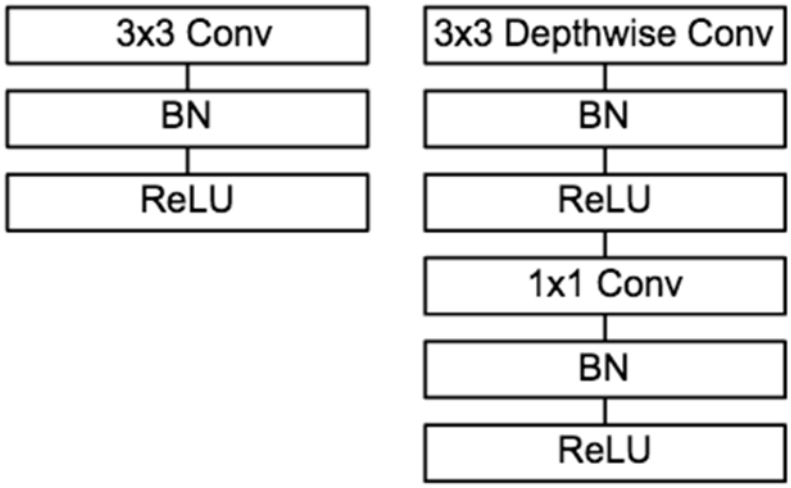

Figure 3.14: block diagram of MobileNet (on the right) and CNN Architectures (on the left)

The convolution unit of MobileNet is shown in the figure above. In Mobilenet, since the 3×3 convolution core is only used in depthwise convolution, 95% of the computation is concentrated in the 1×1 convolution in pointwise convolution. For Caffe and other deep learning frameworks using matrix operation GEMM (General Matrix multiplies).

CHAPTER 4

PROPOSED SKIN CANCER CLASSIFICATION USING MOBILENET CONVOLUTIONAL NETWORKS

Proposed skin cancer classification using MobileNet convolutional networks simulation is done by the Python simulator. Python simulator result is very close to the real life application. The system by which current study did simulation has a properties; Install Memory (RAM is 12 GB). Processor (Intel® Core™ i5-7200CPU@ 2.5 GHZ 2.7 GHz, 64 bits Operating System).

4.1 Skin Cancer Image Dataset

As a first step, create a directory of the images from different sources. In the current dataset, we have 46,466 images which have a size of 224x 224 pixels of RGB images. The dataset is downloaded from Github website .Github is public website and provide free data set for python simulation. The dataset divided by seven classes; each class has around 5,000 images in which 75% for testing and 25 % for validation and after create a validation set using a test because the current work, inside the function, the size (df, test_size=0.20) indicates the percentage of data to be held over for testing and random state is an integer, and then used for a new random state object is seeded (random_state=101) as shown in Table 4.1.

Table 4.1: Skin Cancer image dataset

Class	No of Training Images	No of Validation Images	No of testing images

Nv	5,954	1,545	3312
Mel	5,920	1,134	330
Bkl	5,920	1,036	173
Bcc	5,858	1,098	131
Akiec	5,217	1,040	113
Vasc	5,290	1,020	48
Df	4,410	1,024	29
Total	38,569	7,897	4136

Skin cancer has seven types and which took from the melanoma and non-melanoma image then made a different class. The current work selected high quality images 224 x224 pixel instead of small pixel because python automatically resize images for simulation. Figure4.1 shows the structure of image directory for training and validation. First 224 x 224 input images of the skin cancer are used then MobileNet (CNN) classify our data in different classes. In current work, the network divided input images in seven different classes according to disease. Figure 4.2 illustrates sample 224 by 224 skin cancer images as an input to the CNN.

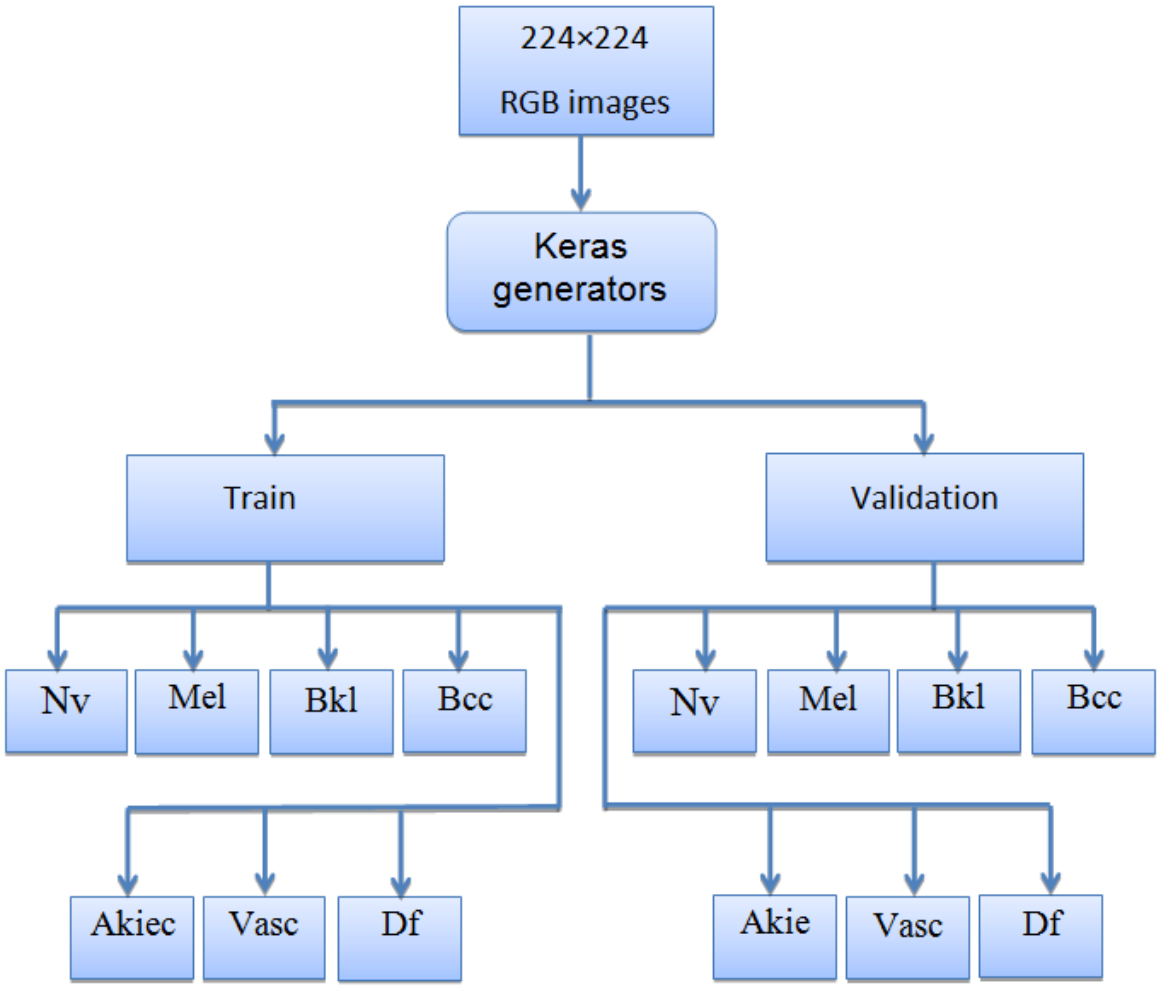

Figure 4.1: Convolutional neural networks classification diagram

4.2 Model validation

The model validation was conducted from the validation set on 4136 unknown sample images. Evaluated micro average methods are used for sum of the individual true positive, false positive and false negative for different sets and apply them to achieve statistics, and weighted average is the type of average where each dataset observation is multiplied by a predetermined weight before calculation is like arithmetic mean for precision, f1 score and recall understanding the model generalized performance, the micro average and weighted average for precision, recall and f1 score for seven classes was evaluated. The Micro average of 0.84, 0.84 and 0.84 and weighted average of 0.86, 0.84 and 0.81, were recorded for recall, f1 score and precision. In current model shows best recall, f1 score and precision

value for NV. The classification of multi class report show weighted average and micro average for recall, f1 score and precision are represented in table 4.2.

Table 4.2: classification of multi class report show weighted average and micro average for recall, f1 score and precision

classes	Precision	Recall	F1-score
Akiec	0.33	0.62	0.43
Bcc	0.48	0.70	0.57
Bkl	0.74	0.11	0.19
Df	0.28	0.36	0.31
Mel	0.42	0.17	0.25
Nv	0.90	0.97	0.94
Vasc	0.89	0.36	0.52
Micro average	0.84	0.84	0.84
Weighted average	0.86	0.84	0.81

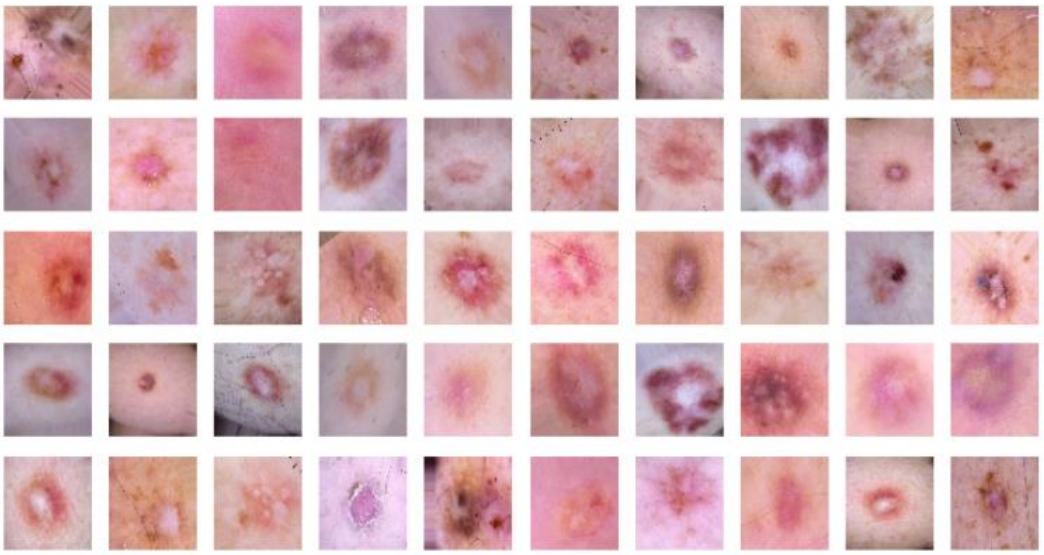

Figure 4.2: Random Input images for training the CNN

4.3 MobileNet CNN Architecture

In current work, the input images to the MobileNet(CNN) that passes from different layers.

Input layer: MobileNet has the ability to use multiple input layer sizes consisting of different width factors. The input sizes of the images in MobileNet ranges 224x224 pixel.

Zero padding layer: non zero boundary conditions are used for most image recognition algorithms however MobileNet uses symmetric padding layers for modelling temporal data that should not infringe on the temporal order. The padding layer is used for maintaining the original data of an image.

Conv2D layer: This implies that a convolution process is in three dimensions but the movement of the filters in an image occurs in 2 dimensions across the image. The Conv2D layer uses a convolved layer to create a Tensor Flow of outputs for the convolution Kernel. Keyword arguments should be inputted when the layer is used as a first layer in a model. A filter size of 3x3 was used for convolutional layer.

Batch Normalize layer: this layer is used as a part of the architecture for normalization of every training mini batch of the model. It enables the use of a higher learning rate. This can sometimes eliminate the process of dropout as it can act as a regularize.

ReLu layer: after batch normalization layer the ReLu layer follows. The ReLu activation layer for MobileNet comprises of a ReLu function. The ReLu function is non-linear and it makes computation efficient for fast network convergence. ReLu prevents activation from getting cumbersome.the work used filter size 2x2 for ReLu layer.

Depth wise Cov2D: the depthwise conv2D allows the first step of the model to be performed in a depthwise spatial resolve in the convolution upon each input channel independently. In depth wise it uses filter size 1x1.

Global-average: this collects the average of pools from each preceding convolutional layers to prevent over fitting found in fully connected layers. This is also implemented to reduce model size and increase the prediction speed of a model**.**

Dropout: this is a method used in deep learning for regularization. To also avoid over fitting in large networks the drop out technique ignores randomly selected neurons in a model during the training period.

Dense: this layer converts the features in an image into a single prediction for each image. It does not require the use of an activation function due to the raw prediction value used for prediction. Finally, images are classified into different classes.

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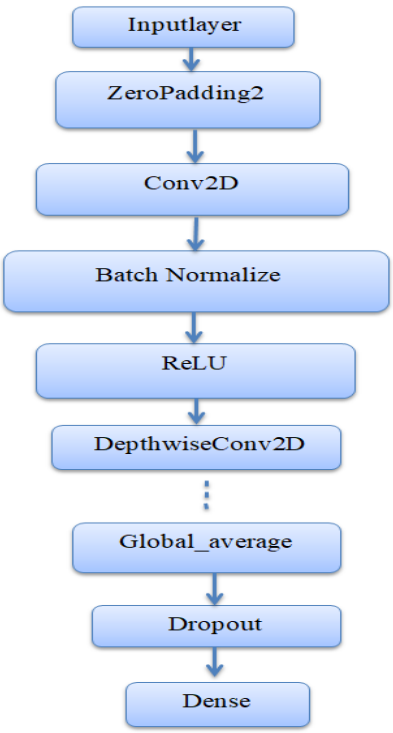
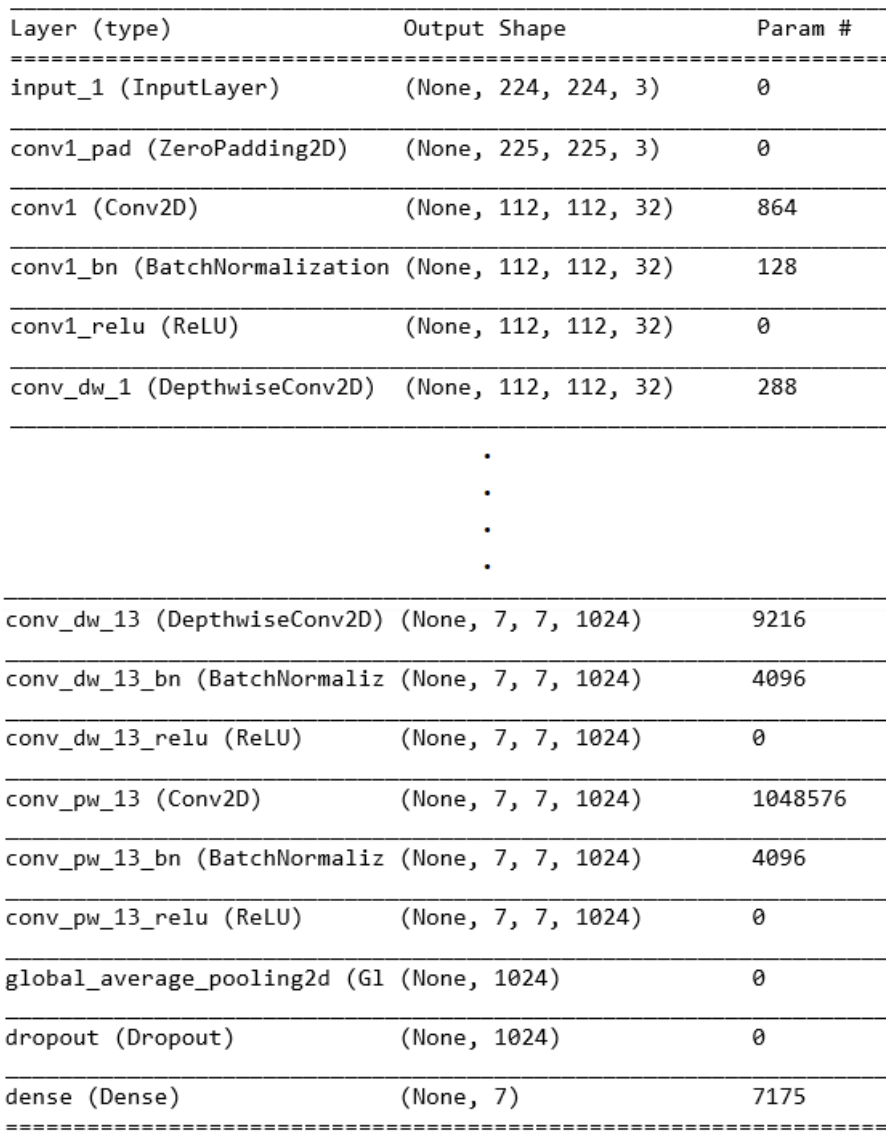


Figure 4.3: traditional Block diagram of Mobilenet **(**CNN) architecture

The structure of MobileNet is built on depth-wise convolutions as mentioned in the previous section except for the first layer that is a full convolution.By defining the network in such simple terms it is easy to explore network topologies to find a good network.All layers are followed by a nonlinearity of batchnorm and ReLU except for the final fully connected layer that has no nonlinearity and feeds for classification into a softmax layer. Figure 4.4 contrasts a layer with regular convolutions, batchnorm and nonlinearity of ReLU with a factorized layer with convolution, 1 x1 point conversion as well as batchnorm

and ReLU after each convolution layer. Counting the convolutions in depth and point as separate layers, MobileNet has 93 layers.



Layer (type)	Output Shape	Param #
input_1 (InputLayer)	(None, 224, 224, 3)	0
conv1_pad (ZeroPadding2D)	(None, 225, 225, 3)	0
conv1 (Conv2D)	(None, 112, 112, 32)	864
conv1_bn (BatchNormalization	(None, 112, 112, 32)	128
conv1_relu (ReLU)	(None, 112, 112, 32)	0
conv_dw_1 (DepthwiseConv2D)	(None, 112, 112, 32)	288
.		
.		
.		
.		
conv_dw_13 (DepthwiseConv2D)	(None, 7, 7, 1024)	9216
conv_dw_13_bn (BatchNormaliz	(None, 7, 7, 1024)	4096
conv_dw_13_relu (ReLU)	(None, 7, 7, 1024)	0
conv_pw_13 (Conv2D)	(None, 7, 7, 1024)	1048576
conv_pw_13_bn (BatchNormaliz	(None, 7, 7, 1024)	4096
conv_pw_13_relu (ReLU)	(None, 7, 7, 1024)	0
global_average_pooling2d (Gl	(None, 1024)	0
dropout (Dropout)	(None, 1024)	0
dense (Dense)	(None, 7)	7175

Figure 4.4: workflow of MobileNet from Python interface

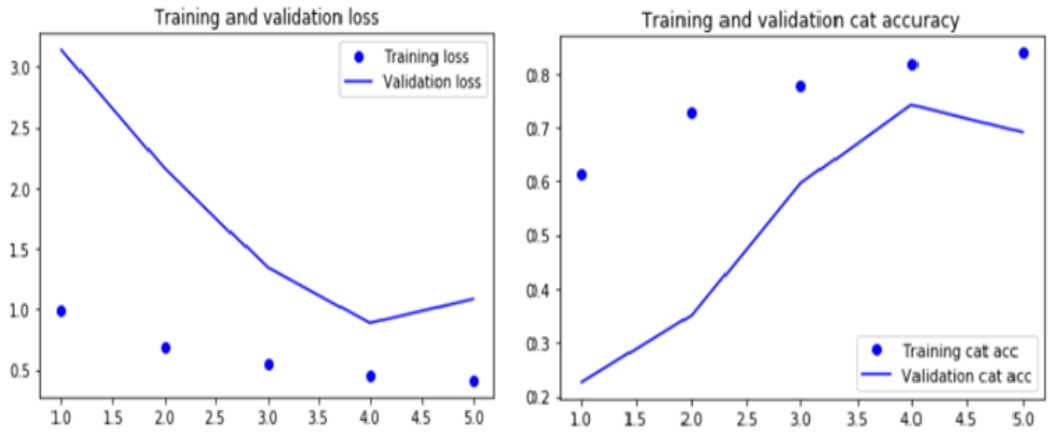
4.4 Train CNN using Training Data and Classifying Images

First, the different CNN architectures are tested in order to find an optimal MobileNet architecture for efficient skin cancer classification. The following sub-sections show the training and validation loss, and training and validation accuracy for different CNN

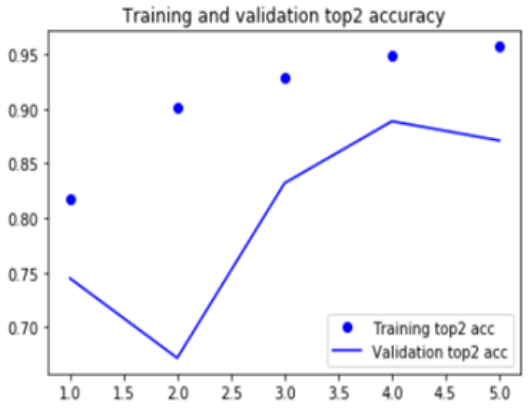
architectures. In the following graphs keep the same CNN layers but the epochs changed for each graph. Some are two layers, some are three layers but the accuracy increase when the number epochs increase.

4.4.1Mobilenet (CNN) using five epochs with two layers

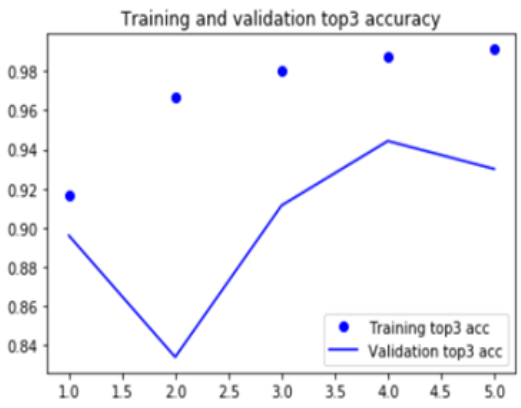
The following graph shows that the validation accuracy and validation loss of the trained networks. In Figure 4.3 two convolutional layers were used. Input layer image size 224x224, convolutional layer filter size 3x3, ReLU layer filter size 2x2 , depth convolutional layer filter size 1x1, batch normalization layer, zero padding layers, dropout layer and dense layer. In Figure 4.3 5 epochs with two convolutional layers was used and the validation with top 3 accuracy is 94. 43% in figure 4.3 c and our top 2 accuracy is 88.88% figure 4.3(b) and cat accuracy is 77.18% figure 4.3(a). Here Mobilenet use 3x3 size filter for convolutional layer 1x1filter size for deptwise layer.



(a): training and validation to loss and cat accuracy



training and validation of top2 (b):

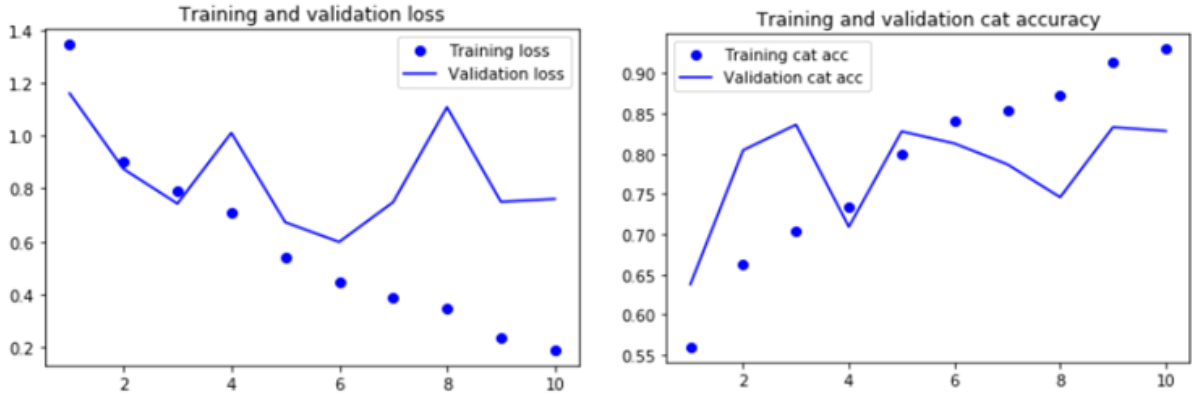


(c) :training and validation of top3

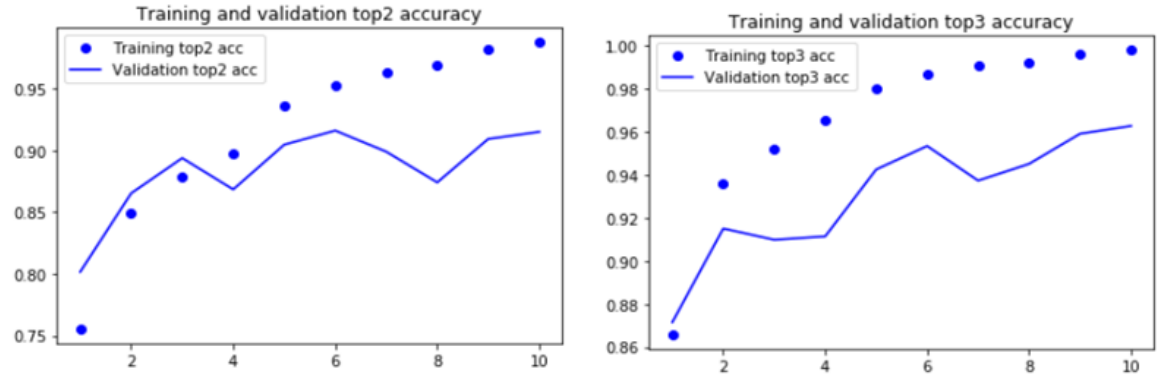
Figure 4.5: Training and validation loss and cat accuracy for MobileNet architecture with two layers and five epochs

4.4.2 MobileNet(CNN) using Three Layers with Ten Epochs

The following graph shows that the validation accuracy and validation loss of the trained networks. In Figure 4.4 three convolutional layers were used of input layer 224x224 pixel image, convolutional layer filter size 3x3 filter, ReLU layer filter size 2x2, depth convolutional layer filter size 1x1, batch normalization layer, zero padding layers, dropout layer and dense layer. In Figure 4.3 10 epochs with three convolutional layers were used and the validation with top 3 accuracy is 96. 26% in figure 4.3 c and the top 2 accuracy is 91.50% figure 4.3(b) and cat accuracy is 82.84% figure 4.3(a). Here Mobilenet use 3x3 size filters for convolutional layer 1x1filter size for deptwiselyer.



(a): training and validation to loss and cat accuracy



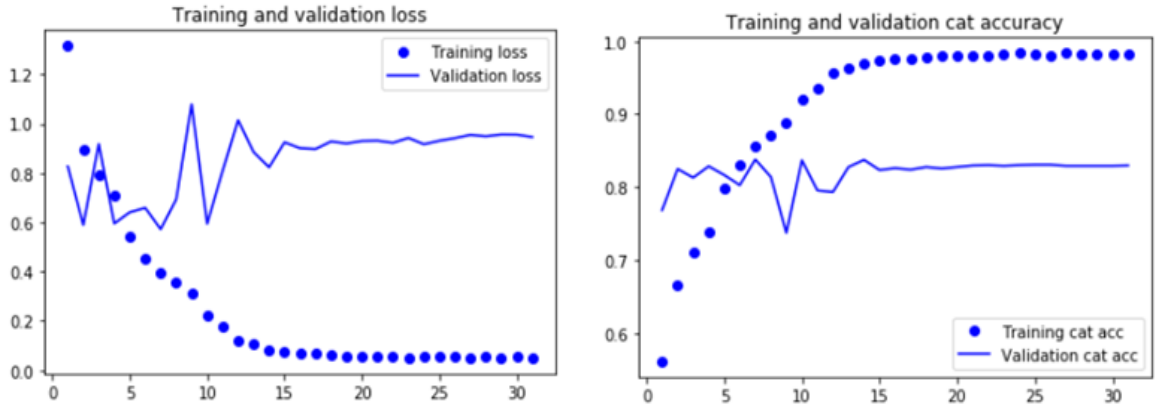
(b) : Training and validation of top2

(c) :Training and validation of top3

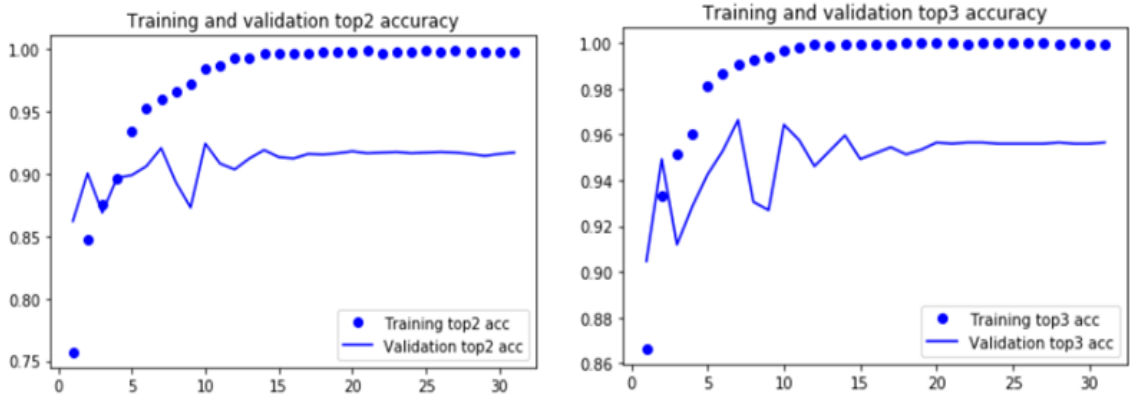
Figure 4.6: Training and validation loss and cat accuracy for MobileNet architecture with three layers and ten epochs

4.4.3 Mobilenet (CNN) using Six Layers with Thirty One Epochs

The following graph shows that the validation accuracy and validation loss of the trained networks. In Figure 4.3 six convolutional layers of input layer were used, convolutional layer filter size 3x3, ReLU layer filter size 2x2 , depth convolutional layer filter size 1x1, batch normalization layer, zero padding layers, dropout layer and dense layer. In Figure 4.5 31 epochs with five convolutional layers were used and our validation with top 3 accuracy is 97. 00% in figure 4.5© and our top 2 accuracy is 92.07% figure 4.5(b) and cat accuracy is 83.78% figure 4.5(a). Here Mobilenet use 3x3 size filter for convolutional layer 1x1filter size for deptwiselyer.



(a): training and validation to loss and cat accuracy



(b): training and validation of top2 (c) :training and validation of top3

Figure 4.7: Training and validation loss and cat accuracy for MobileNet architecture

with six layers and thirty one epoch

CHAPTER 5

EVALUATIONS

As explained in section 4.1, 46,466 224x 224 RGB images were used for training and validation. In particular, 75% for testing and 25% for validation, in total, 38,569 were used for training and 7,897 for validation. For the same dataset, different MobileNet architectures are tested and the results are given in the sub-sections. The set of training is used to train the model, while the validation set is only used to assess the performance of the model. Training is a set of instances used for learning that suit the classifier's parameters. Gray scale was used however compared to RGB it had no effect on the result.

The accuracy of categorical, top2 and top3 accuracy was used to assess the efficiency of the MobileNet model; Model evaluation was performance by calculating categorical accuracy, top2 accuracy, top3 accuracy and confusion matrix. Top-N accuracy means that the predicted correct class should be in the Top-N probabilities for it in order to count as "correct". As an example, suppose I have a dataset of images. If the top-3 accuracy is taken for this, the correct class only needs to be in the top three predicted classes to count as correct. Top 2 or to top 3 accuracy means that the predicted correct class should be in the Top-2 or in the Top-3 probabilities respectively.

5.1 Accuracy Results for Two Convolutional Layers with Five Epochs

In Table 5.2, validation accuracies for top 3 and top 2 are presented. If the top-3 or top 2 accuracy are taken, the correct class only needs to be in the top two or three predicted classes to count as correct. The top 3 accuracy is 94.43% and the top 2 accuracy is 88.88%. The graphical results also shown in Figure 5.1. Here the Mobilenet use 3x3 filters size for two convolutional layers and 1x1filter size for deptwise layer of our model.

Table 5.1: Validation accuracy using two convolutional layers with five epochs

epoch	Layers	val_cat_acc:	val_top_2_acc:	val_top_3_acc:
5	2	74.18	88.84	94.43

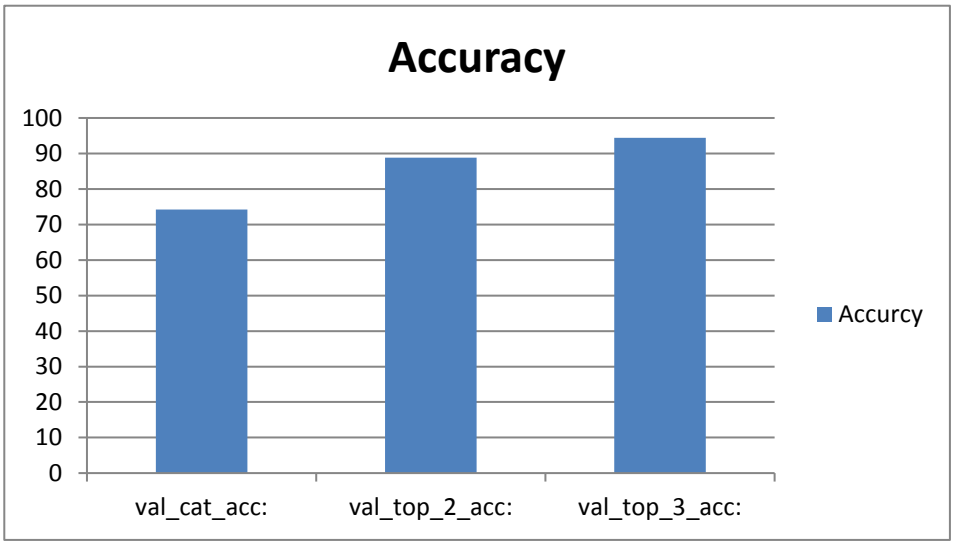
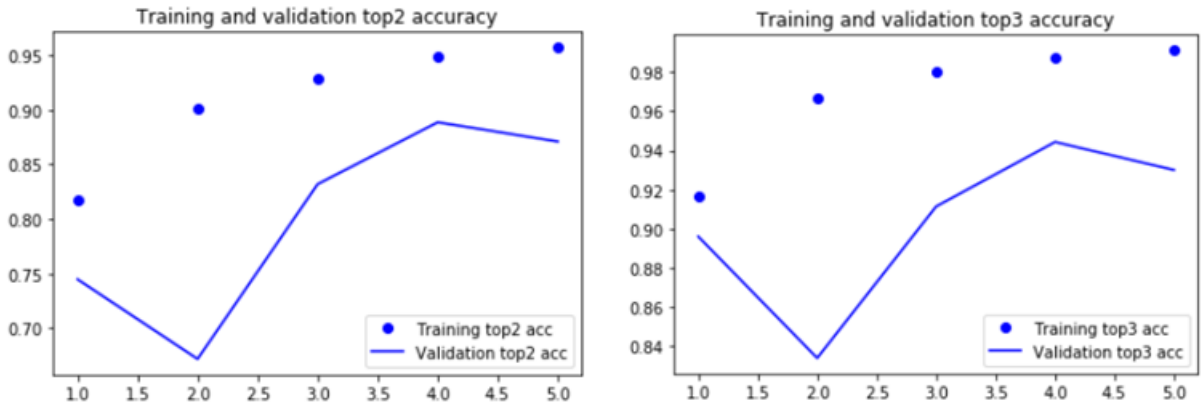


Figure 5.1: Validation accuracy using two convolutional layers with five epochs



(a) Training and validation of top2 (b) training and validation of top3

Figure 5.2: Training and validation accuracy for top 2 and top 3

5.2. Accuracy Results for Three Convolutional with Ten Epochs

In Table 5.3 three layers with 10 epochs are used and the validation with top 3 accuracy is 96. 26% 4.3 and our top 2 accuracy is 91.50% and cat accuracy is 82.84%.The graphically result also show in Figure 5.3. Here the Mobilenet use 3x3 filters size for three convolutional layers and 1x1filter size for deptwise lyer of our model. Results show that comparing to the model with two layers, categorical accuracy increase ~8% and the top-3 accuracy increase (~2%). However, the top-2 accuracy decrease ~6%.

Table 5.2: Validation accuracy using three convolutional layers with ten epochs

Epoch	Layers	val_cat_acc:	val_top_2_acc:	val_top_3_acc:
10	3	82.43	82.91	96. 26

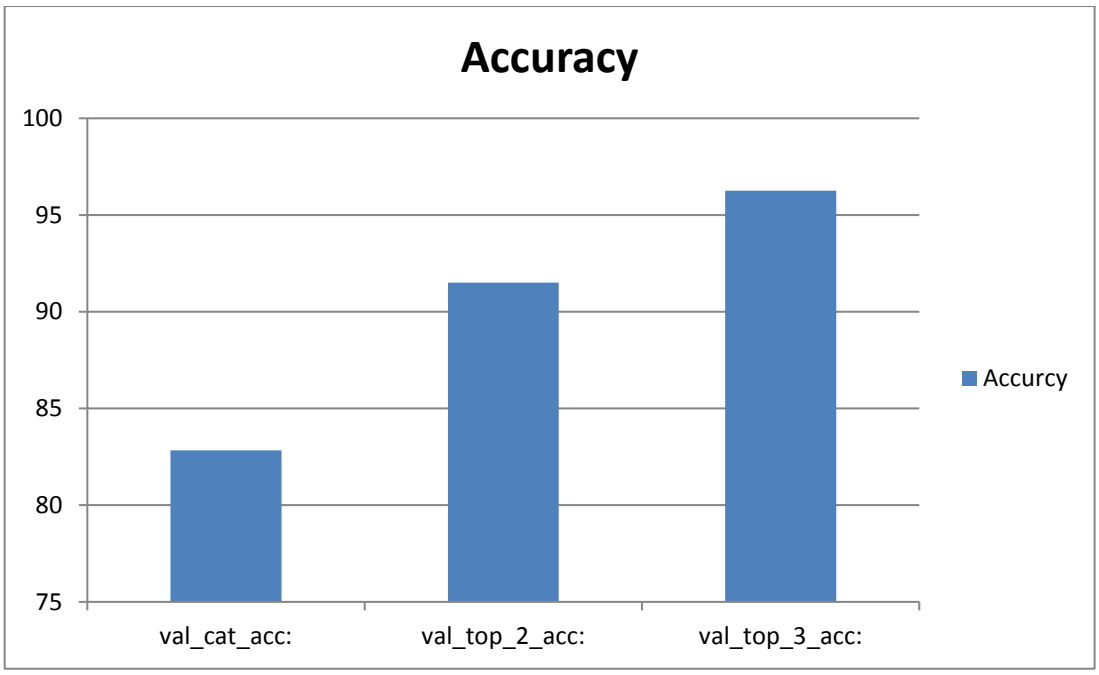
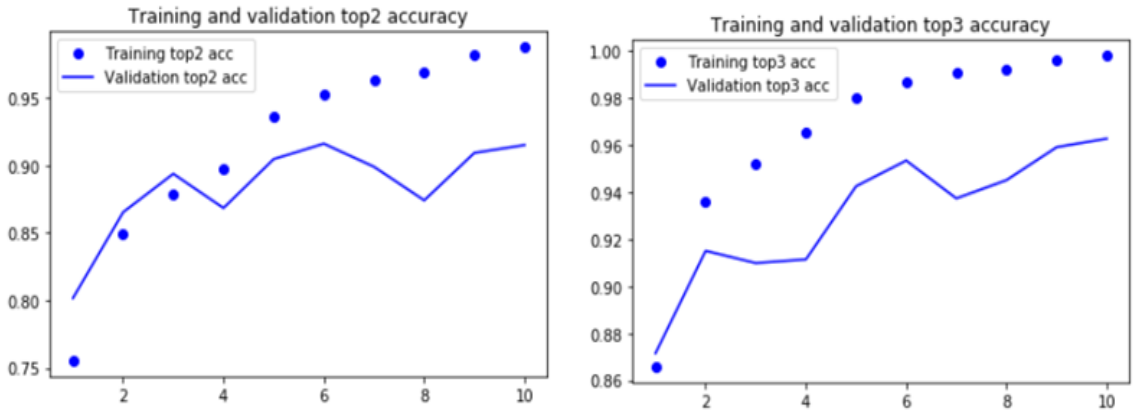


Figure 5.3: Validation accuracy using 10 epoch and 3 layers



(a) Training and validation of top2 (b) training and validation of top3

Figure 5.4: Training and validation accuracy for top 2 and top 3

5.3 Accuracy Result for Six Convolutional Layers with Thirty One Epochs

In Table 5.4 six layers with 31 epochs are used and our validation with the top 3 accuracy is 97.00 and our top-2 accuracy is 92.07% and cat accuracy is 83.785%. The graphically results also shown in Figure 5.5 Here the Mobilenet use 3x3 filters size for six convolutional layers and 1x1filter size for deptwise layer of our model. Results show that among the other MobileNet models. The model with six layers performs the best with the highest categorical accuracy, the top-2 accuracy and the top-3 accuracy.

Table 5.3: Validation accuracy using six convolutional layers with thirty one epochs

Epoch	Layers	val_cat_acc:	val_top_2_acc:	val_top_3_acc:
31	Six layers	83.78	92.07	97.00

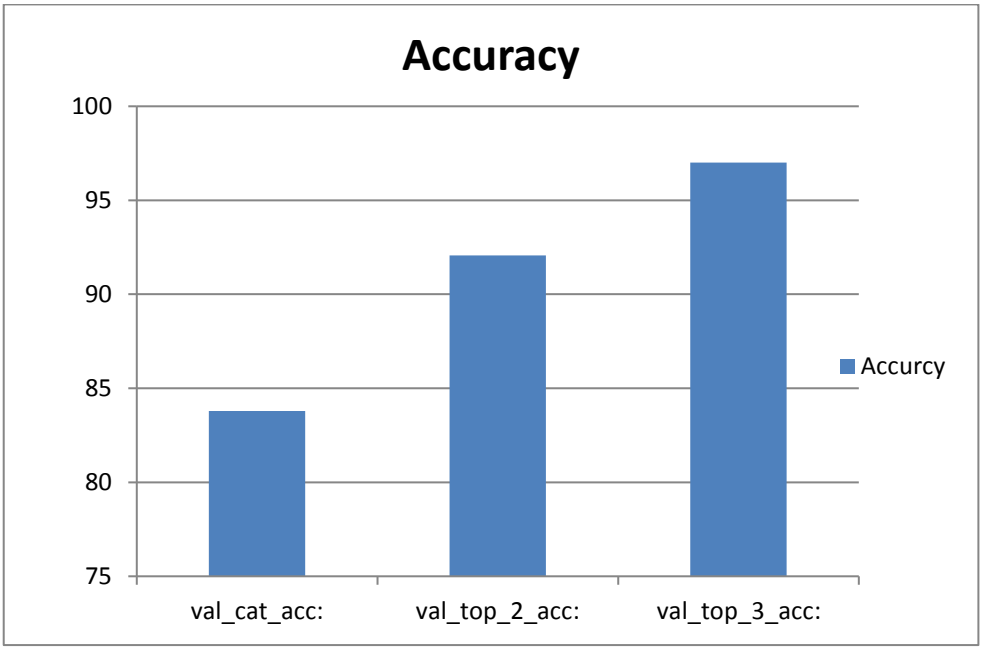
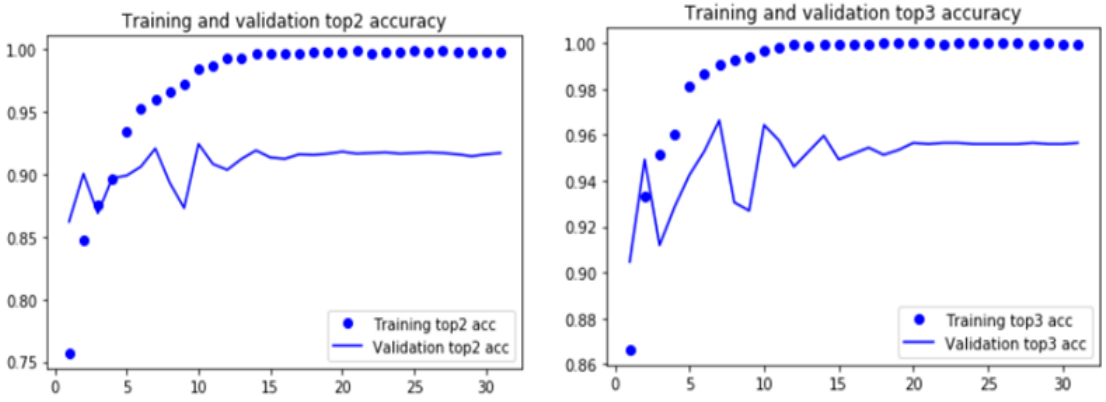


Figure 5.5: Validation accuracy using 31 epoch and six layers



(a) Training and validation of top2 (b) Training and validation of top3

Figure 5.6: Training and validation accuracy for top 2 and top 3

5.4 Comparison with the Existing Works

When the work is compared to the existing work the accuracy from different research paper, the work used MobileNet(CNN) deep learning and the existing work they are used CNN deep leaning, first all the accuracy are added and after it is divided by 3.The table shows that percentage (%) of accuracy. The accuracy result of the previous work decrease when increases the number of images are decreases. But in our work the accuracy increases when there is an increase in the number of epochs. Table number 5.5 shows our result with different images and table 5.5 shows the average of our work and existing work.

The first existing work they Use only 399 images to arrange melanomas versus nevus typed. These methods achieve the accuracy is 93.96% (Pomponiu et al., 2016).

The second Use 2624 Universal Skin Imaging Coordinated Effort (ISIC) dermatoscopic images. In this method the accuracy is 73.90 %(Codella et al., 2015).

the third use 12,378 open-source dermoscopic images and they achieve 70.00% (Brinker et al., 2019).

Table 5.4: Accuracy of existing works

Method	**No of Images**	**Accuracy**
(Pomponiu et al., 2016)	399	93.96
(Codella et al., 2015)	2624	73.90
(Brinker et al., 2019)	12378	70.00

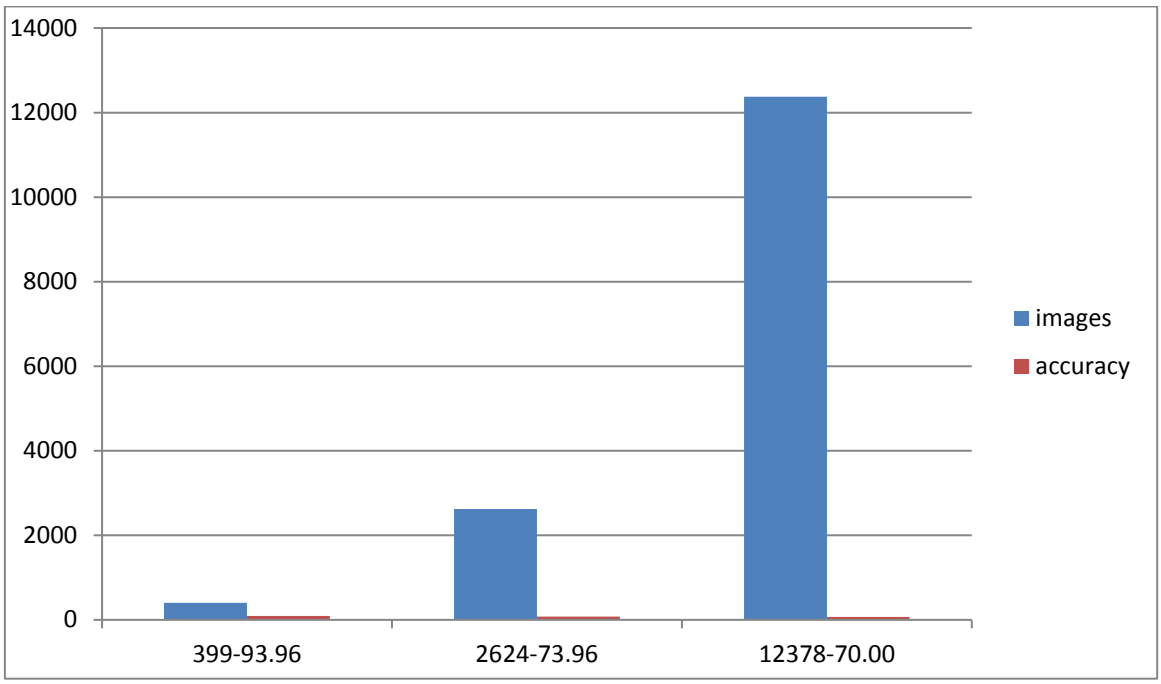


Figure 5.7: images and accuracy of previous work

5.5. Time Evaluations and Number of Convolutional Layers

The training and validation performance for the 2 layer has the Top 3 accuracy of 94.43%, which takes 20 hours of training and that is less than 3 layers. 3 Layers has the Top 3 accuracy of 96.26% and takes 56 hours of training. The next layer which represents 6 layers is seen to perform better than the previous ones with the Top 3 accuracy of 97.00% and it takes 96 hours of training.

Table 5.5: Time Evaluations and layers

Layers	Cat accuracy	Top2 accuracy	Top3 accuracy	Training Time
2 layers	74.18%	88.84%	94.43%	20 hours
3 layers	82.43%	82.91%	96.26%	56 hours
6 layers	83.78%	92.07%	97.00%	96 hours

5.6 Comparing with Existing Works in Terms of Accuracy

The comparison of the present research with other related work is shown in Table 5.7. The most of the existing works perform classification of two or three skin cancer types and their accuracies vary between 66% and 81%. On the other hand, seven types of skin cancer images were used, and results show that the work achieves very competitive accuracies comparing to the existing works. Although the seven skin cancer classes was analysed, the work achieve a top 3 accuracy is 97.00%,top 2 accuracy of 92.07% and categorical accuracy of 81.2%, which can help doctors to diagnose the right disease. Furthermore MobileNet technique is more effective considering the quicker processing capacity and lightweight architecture of the MobileNet model. From previous papers are used CNN (Ruiz et al, 2011) and (Harangi et al 2018) the accuracy of CNN is about 80% which compared to the work with MobileNet is quite low for its use in small number of images. But the work of (Bi et al., 2017) and (Mahbod et al., 2019) are very good but they have very high accuracy but they classify 2 or 3 classes and we classify 7 classes. This work applied more number of images and the accuracy is 97%.

Table 5.6: Comparison with the existing work

year	classifier	No. of class (skin	Cat Accuracy	Top-2 Accuracy	Top-3 Accuracy

		cancer types)			
2011	KNN(Ramlakhan et al.,2011)	2	66.7%		
2011	KNN (Ruiz et al., 2011)	2	73.47%	80.6%	86.73%
2016	CNN with GoogleNet&VggNet (Harangi et al.,2016)	3	79.3%	79.9%	80.6%
2017	CNN (Esteva et al.,2017).	3		69.4%	72.1%
2017	CNNs (Bi et al.,2017).	3	90.96%	97.00%	97.60%
2018	CNN (Rogers et al., 2018).	6	82.26%	88.82%	90.40%
2109	CNNs (Mahbod et al.,2019)	2		87.3%	95.5%
2019	Proposed Mobilenet model	7	83.78%	92.07%	97.00%

5.6 Confusion Matrix

A confusion matrix also recognized as an error matrix in the field of machine learning and specifically the issue of statistical classification. A confusion matrix is a table that is often used to define the performance of an algorithm's classification system (or "classifier") on a collection of test information for which the real values are known. It enables confusion between classes to be easily identified, e.g. one class is frequently mislabelled as the other. Most efficiency measurements are calculated from the matrix of confusion. Following Figure shows the confusion matrix of our result which was gotten it from our data set simulation test.

The network sections speak to the expectation names and the columns speak to the genuine marks. The perplexity lattice is consistently a 2-D exhibit of shape [n, n], where n is the quantity of substantial names for a given grouping task. Both forecast and names must be 1-D varieties of a similar shape all together for this capacity to work.

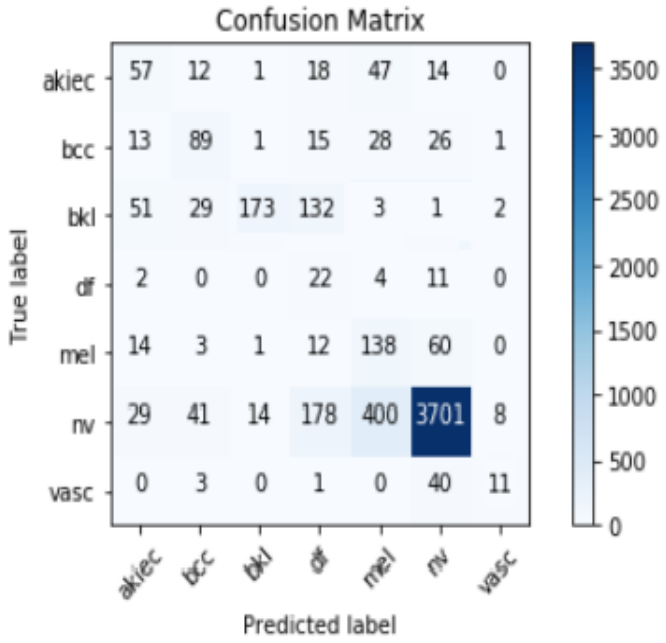


Figure 5.8: Confusion matrix MobileNet using six layers with thirty one epochs

CHAPTER 6

CONCLUSION AND FUTURE WORK

After study and implementation of deep learning in the field of cancer diseases it is concluded that deep leaning while using MobileNet provide very competitive results comparing to the state-of-the-art. First these images were downloaded from Github and then more images were downloaded from different sites to increase the number of testing images. Then the network is trained for the test of different skin cancer diseases. After training the network was able to classify the skin cancer images into different classes. For this current work 97% accuracy was achieved with a MobileNet architecture with three convolutional layers. MobileNet is a lightweight system engineering which is progressively reasonable for portable and inserted based vision applications where there is absence of figure control. The high percentage is largely due to the usage of Mobilenet and added layers and epochs.

Compared to previous works, this work uses more number of images in order to achieve better performance. However during the study, the image dataset require licences before more images can be downloaded, which was a problem.

Once improvements are made on the MobileNet algorithms for the skin cancer in the field of medical the results can be improved. So nowadays deep learning is the best solution of skin cancer diseases classification and recognition of cancerous diseases. In the future MobileNet for skin cancer disease would help medical stakeholders to avoid the conventional lab and in-vivo tests. Without testing or without the use of x rays skin cancer would be automatically detected using the MobileNet algorithm embedded in mobile. This saves time; its simplicity makes it easy for the public without the need of a doctor.

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Appendix

```
fromnumpy.random import seed

seed(101)

fromtensorflow import set_random_seed

set_random_seed(101)

import pandas as pd

importnumpy as np

importtensorflow

romtensorflow.keras.layers import Dense, Dropout

fromtensorflow.keras.optimizers import Adam

fromtensorflow.keras.metrics import categorical_crossentropy

fromtensorflow.keras.preprocessing.image import ImageDataGenerator

fromtensorflow.keras.models import Model

fromtensorflow.keras.callbacks import EarlyStopping, ReduceLROnPlateau, ModelCheckpoint import os from sklearn.metrics import confusion_matrix

fromsklearn.model_selection import train_test_split

importitertools

importshutil

importmatplotlib.pyplot as plt

%matplotlib inline

base_dir = 'base_dir'

os.mkdir(base_dir)

train_dir = os.path.join(base_dir, 'train_dir')

os.mkdir(train_dir)

val_dir = os.path.join(base_dir, 'val_dir')

os.mkdir(val_dir)

nv = os.path.join(train_dir, 'nv')

os.mkdir(nv)

mel = os.path.join(train_dir, 'mel')
```

```
os.mkdir(mel)
bkl = os.path.join(train_dir, 'bkl')
os.mkdir(bkl)
bcc = os.path.join(train_dir, 'bcc')
os.mkdir(bcc)
akiec = os.path.join(train_dir, 'akiec')
os.mkdir(akiec)
vasc = os.path.join(train_dir, 'vasc')
os.mkdir(vasc)
df = os.path.join(train_dir, 'df')os.mkdir(df)
nv = os.path.join(val_dir, 'nv')
os.mkdir(nv)
mel = os.path.join(val_dir, 'mel')
os.mkdir(mel)
bkl = os.path.join(val_dir, 'bkl')
os.mkdir(bkl)
bcc = os.path.join(val_dir, 'bcc')
os.mkdir(bcc)
akiec = os.path.join(val_dir, 'akiec')
os.mkdir(akiec)
vasc = os.path.join(val_dir, 'vasc')
os.mkdir(vasc)
df = os.path.join(val_dir, 'df')
os.mkdir(df)
df_data['duplicates'].value_counts()
df = df_data[df_data['duplicates'] == 'no_duplicates']
df.shape
y = df['dx']
_, df_val = train_test_split(df, test_size=0.17, random_state=101, stratify=y)
```

```
df_val.shape
df_val['dx'].value_counts()
df_train = df_data[df_data['train_or_val'] == 'train']
print(len(df_train))
print(len(df_val))
df_train['dx'].value_counts()
df_val['dx'].value_counts()
print(len(os.listdir('base_dir/train_dir/nv')))
print(len(os.listdir('base_dir/train_dir/mel')))
print(len(os.listdir('base_dir/train_dir/bkl')))
print(len(os.listdir('base_dir/train_dir/bcc')))
print(len(os.listdir('base_dir/train_dir/akiec')))
print(len(os.listdir('base_dir/train_dir/vasc')))
print(len(os.listdir('base_dir/train_dir/df')))
print(len(os.listdir('base_dir/val_dir/nv')))
print(len(os.listdir('base_dir/val_dir/mel')))
print(len(os.listdir('base_dir/val_dir/bkl')))
print(len(os.listdir('base_dir/val_dir/bcc')))
print(len(os.listdir('base_dir/val_dir/akiec')))
print(len(os.listdir('base_dir/val_dir/vasc')))
print(len(os.listdir('base_dir/val_dir/df')))
def plots(ims, figsize=(12,6), rows=5, interp=False, titles=None):
if type(ims[0]) is np.ndarray:
ims = np.array(ims).astype(np.uint8)
if (ims.shape[-1] != 3):
ims = ims.transpose((0,2,3,1))
    f = plt.figure(figsize=figsize)
cols = len(ims)//rows if len(ims) % 2 == 0 else len(ims)//rows + 1
for i in range(len(ims)):
sp = f.add_subplot(rows, cols, i+1)
```

```
sp.axis('Off'

sp.set_title(titles[i], fontsize=16)

plt.imshow(ims[i], interpolation=None if interp else 'none')

plots(imgs, titles=None)

x = mobile.layers[-6].output

x = Dropout(0.25)(x)

predictions = Dense(7, activation='softmax')(x)

model = Model(inputs=mobile.input, outputs=predictions

fromtensorflow.keras.metrics import categorical_accuracy, top_k_categorical_accuracy

def top_3_accuracy(y_true, y_pred):

returntop_k_categorical_accuracy(y_true, y_pred, k=3)

def top_2_accuracy(y_true, y_pred):

returntop_k_categorical_accuracy(y_true, y_pred, k=2)

filepath = "model.h5"

checkpoint = ModelCheckpoint(filepath, monitor='val_top_3_accuracy', verbose=1,

save_best_only=True, mode='max')

reduce_lr = ReduceLROnPlateau(monitor='val_top_3_accuracy', factor=0.5, patience=2,

verbose=1, mode='max', min_lr=0.00001)

callbacks_list = [checkpoint, reduce_lr]

history = model.fit_generator(train_batches, steps_per_epoch=train_steps,

class_weight=class_weights,

validation_data=valid_batches,

validation_steps=val_steps,

epochs=30, verbose=1,

callbacks=callbacks_list)

val_loss, val_cat_acc, val_top_2_acc, val_top_3_acc = \

model.evaluate_generator(test_batches,
```

```
steps=len(df_val))
print('val_loss:', val_loss)
print('val_cat_acc:', val_cat_acc)
print('val_top_2_acc:', val_top_2_acc)
print('val_top_3_acc:', val_top_3_acc)
importmatplotlib.pyplot as plt

acc = history.history['categorical_accuracy']
val_acc = history.history['val_categorical_accuracy']
loss = history.history['loss']
val_loss = history.history['val_loss']
train_top2_acc = history.history['top_2_accuracy']
val_top2_acc = history.history['val_top_2_accuracy']
train_top3_acc = history.history['top_3_accuracy']
val_top3_acc = history.history['val_top_3_accuracy']
epochs = range(1, len(acc) + 1)
plt.plot(epochs, loss, 'bo', label='Training loss')
plt.plot(epochs, val_loss, 'b', label='Validation loss')
plt.title('Training and validation loss')
plt.legend()
plt.figure()
plt.plot(epochs, acc, 'bo', label='Training cat acc')
plt.plot(epochs, val_acc, 'b', label='Validation cat acc')
plt.title('Training and validation cat accuracy')
plt.legend()
plt.figure()
plt.plot(epochs, train_top2_acc, 'bo', label='Training top2 acc')
plt.plot(epochs, val_top2_acc, 'b', label='Validation top2 acc')
plt.title('Training and validation top2 accuracy')
plt.legend()
```

```
plt.figure()
plt.plot(epochs, train_top3_acc, 'bo', label='Training top3 acc')
plt.plot(epochs, val_top3_acc, 'b', label='Validation top3 acc')
plt.title('Training and validation top3 accuracy')
plt.legend()
plt.show
```