CLASSIFICATION OF SKIN CANCER IMAGES USING CUSTOM CONVOLUTIONAL NEURAL NETWORK

End Sem Evaluation Report submitted in Partial fulfillment of the requirements

for the degree of

M.Tech in Computer Science & Engineering

by

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DECLARATION

I, Talapally Sandeep Kumar (212CS033), student of M.Tech (Computer Science & Information Security), hereby declare that 3rd semester progress report titled **CLASSIFICATION OF SKIN CANCER IMAGES USING CUSTOM CONVOLUTIONAL NEURAL NETWORK** which is submitted by me to the Department of Computer Science & Engineering, National Institute of Technology, Karnataka, Surathkal in fulfillment of the requirement of the degree of Master of Technology in Computer Science and Engineering , is not copied from any source without proper citation. This work has not previously formed the basis for the award of any Degree, Diploma, Fellowship or other similar title or recognition.

Place: Surathkal
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CERTIFICATE

I hereby certify that the Project titled **CLASSIFICATION OF SKIN CANCER IMAGES USING CUSTOM CONVOLUTIONAL NEURAL NETWORK** which is submitted by **Talapally Sandeep Kumar (212CS033)**, for fulfillment of the requirements for the degree of Master of Technology in Computer Science and Engineering , is a record of the project work carried out by the students under my guidance & supervision. To the best of my knowledge, this work has not been submitted in any part or fulfillment for any Degree or Diploma to this University or elsewhere.

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Abstract

Dermatological disorders, especially human skin ailments, have been growing in recent decades for numerous factors. Skin cancer is regarded for worst form of cancer. Unrepaired deoxyribonucleic acid (DNA) in skin cells generates genetic flaws or mutations on the skin, which leads to skin cancer. Because skin cancer develops gradually to other regions of the body, it may be treated in the initial stages, which is why it is best diagnosed early. The rising number of skin cancer cases, high death rate, and high expense of medical treatment need rapid recognition of its signs. Having the significance of this vast number of issues, researchers have devised a range of skin cancer early detection technologies. Lesion features such as symmetry, colour, size, shape, and so on. Humans who have been exposed to the sun for a long period of time are more prone to have skin cancer, which is described as an abnormal proliferation of skin cells. The classification of dermatoscopic photos is necessary for the early detection of this disorder, making it an intriguing research subject.The great majority of these disorders are contagious and reliant on visual perceptions. Despite the fact that various study have proven promising results on the photo classification issue, only a few studies compare traditional machine learning models with modern deep learning models with multiple metrics on human skin disease classification. To change the input photographs into the correct format for all models, we undertake image pre-processing, image scaling, image interpolation, and image augmentation. RestNet50 exceeds other deep learning and traditional machine learning algorithms by a large margin in all parameters studied, including F-measure, accuracy, precision, and recall.

Dermatological disorders are shooting up in recent decades. Most of these diseases spread from individual to individual as well as depend on visual outlooks; dermatological diseases of one type occur on some portion of the body might differ on another portion of the body in overall look, illnesses of various types found on one portion of the body may resemble on other parts of body. As a result, it need to be evaluated early on to prevent it from spreading. The image processing segment relates to enhancement and the eradication of undesirable areas, which is proven to be required before further processing, otherwise the output efficiency will decline. When examined on those datasets, the validation accuracy was observed to be 74.1%, and after performing fine tuning, it was determined to be 76.3%. After examining on those datasets the validation accuracy was observed to be 74.1%. After fine tuning it was observed 76.3% .Skin cancer is crucial and important cause of death globally. Melanoma and non-melanoma are the two forms of skin cancer. Early detection of these lesions has the potential to improve the cure rate to 90%. The considerable likeness between diverse kinds of skin lesions makes visual examination difficult and may result in inaccurate inquiry. As a consequence, for skin lesion classification, an automated method is essential. This classification system took use of image processing and artificial intelligence tools. The prior computer-aided systems for dermatological picture organisation had two main shortcomings. First, there is little data. The imaging process is the second tough challenge, with skin photos taken using a specialised device, dermoscopy, and other medical images, such histology images, acquired using microscope and biopsy. To classify skin photos, earlier techniques involved considerable pre-processing, segmentation, and feature extraction procedures. There are various skin disorders to which it is difficult to identify. Deep learning is helping to uncover more effective approaches for excellent dermoscopic analysis.

Millions of individuals worldwide suffer from numerous skin issues. People suffer terribly from acne to eczema. A little steam cut on the skin may sometimes evolve into a big problem, or even a little infection that causes serious health risks sometimes. Some skin illnesses are so infectious that one person may infect another just by shaking hands or using a handkerchief. A complete diagnosis may lead to proper medicine, which may alleviate the misery of persons who are suffering and enhance awareness. This research focuses on the work done so far in deep learning on skin cancer categorization.

Chapter 1

Introduction

Skin cancers and diseases are the most frequent types of illness in this decade. Since the skin is the body's biggest organ, it is extremely evident that skin cancer is the most typical disease in people. Skin functions as the protective layer for body and also plays an important role in temperature control. It protects the body against several outside dangerous things such as viruses and bacteria , chemical damage, and so on. As a consequence, protecting skin health is vital to a person's overall health. Human skin is sensitive to injury from numerous substances that it is exposed to, and genetics play a key role as well. The most prevalent causes of skin illnesses are fungal,viral, or allergy, but diagnosing and treating these diseases has proved to a significant event in the area of health industry. Early indications of skin cancer suggest that the disease has also not gone toward a more critical level and it may enhance the likelihood of survival while reducing its expenditure. Because treatment is costly, skin infections should be discovered and treated as soon as practical. Several projects have been undertaken to bring traditional medicine into practise in various parts of the globe, notably in less technologically advanced nations. Because distinct skin lesions develop in different persons, with differences in skin textures and tones, the prevalence of skin sickness may vary depending on the colour and length of the lesion's spread. Human observation alone is ineffective for properly diagnosing diseases in the absence of suitable identification processes.

In medical science, there are various techniques available for identifying skin issues. However, automated diagnosis which is computer realated, is considerably more beneficial for decision assistance in medical area and pumps up the complete procedure. People wouldnt suffer much,if we deploy such an automated system in healthcare domains. This solution is not painful. The skin is the largest organ in our body which encompasses the various nerves, muscles, blood vessels. It is the body's protective shield as well plays a vital role in regulating the body temperature. It protects the body for various external harmful substances like pathogens, viruses, chemical damage and so on. Therefore maintaining the health of the skin is important of a person's well being. The skin of humans are prone to damage from various substances that it is exposed to as well as the genetics of one's own body plays an important role too. The predominant causes of skin diseases could be viral, fungal or allergic but detection and alleviation of these diseases have proven to be a tedious task in the field of medicine. Skin cancer has recently been identified as one of the most common cancers worldwide. The prevalence of skin diseases is rising, and early detection is critical to a positive outcome. Because skin cancer is the most common type of cancer, early identification of skin cancer denotes that cancer has not progressed to a more advanced stage and may possibly increase the percentage of survival while lowering the cost. As the treatment is expensive, it's advisable to get the skin infections identified and treated at an earlier stage. There have been several attempts to put traditional medicine into practice in several regions of the world, particularly in countries that aren't technologically sophisticated as others.

Efforts have been hampered by obstacles such as the high cost of production. medical equipment and instruments, as well as a paucity of medical personnel expertise. A skin lesion is a section of skin that has developed unnaturally and in certain situations, skin cancer-prone. It is not known to the general people, the type of skin disease or the stage of infection that they are experiencing. In some instances, the infection shows symptoms only after several months, during which the disease spreads further. Even, dermatologists at times find the detection of skin diseases challenging. Though, there have been advancements in the field of science using lasers and medical practices based on photonics, that have been extremely helpful in detection of these diseases, the extensive laboratory tests involved makes the methodology very expensive for people to acquire. Skin diseases have a lot of variations in them ranging from Acne, Atopic dermatitis, Psoriasis, Hives, Eczema, Poison Ivy etc. So, it is extremely important to use a dataset that has a wide variety of images of various prevalent diseases. The solution proposed must be able to identify and segregate the various diseases at a good accuracy using the fine-tuned custom model that is build.

1 Motivation

Esteva et al. [11] were first to report about how the image classifier convolutional neural netwok (CNN) can achieve the performance similar to the 21 board-certified dermatologists for identification of malignant lesions. The 3-way disease partition algorithm was designed to classify a given skin lesion to be malignant, benign or non-neoplastic. Also, 9-way disease partition was performed to classify a given lesion into one of the 9 mentioned categories. The state-of-the art InceptionV3 CNN architecture was used for skin lesion classification [11] has concluded that the CNN can outperform human experts if it is trained with enough data. Also, [11] has concluded that the CNN can outperform human experts if it is trained with enough data.

Zhang et al. [12] also used InceptionV3 architecture with modified final layer to classify 4 diseases. The model was trained on two nearly similar datasets of dermoscopic images. Authors [12] concluded that misclassification can occur due to presence of multiple disease lesions on the single skin image.

Rehman et al. [13] have proposed CNN architecture by setting 16 different filters of 7*7 kernel size with pooling layers for down sampling. The proposed model was trained for malignant and benign category of diseases namely; melanoma, Seborrheic keratosis and nevus. The RGB channels of the segmented image are normalized with zero mean and unit variance. This normalized matrix was fed to CNN for feature extraction, further the fully connected layer consists of 3 layer ANN classifier which classify the skin lesion being banign or malignant.

Chapter 2

Literature review

1 Literature Survey

Skin disorders have long been one of the most prominent sorts of health difficulties that individuals have addressed. Skin illness is often diagnosed based on physicians' experience and skin biopsy findings, that is a time-taking process. To increase diagnosis accuracy and overcome the absence of human specialists, an autonomous system for skin disease detection and categorization utilising photographs is required. Skin disease classification from a photograph is a big difficulty that is heavily dependant upon that elements of the illness examined so that appropriately can be named. Various skin illnesses exhibit roughly equal aesthetic traits, making it more difficult to detect essential components from an image. Accurate image analysis of such disorders improves diagnosis, reduces time for diagnosis, and gives a better and more inexpensive cost therapy for patients. This article offers several approach and strategies for skin disease categorization, including standard or bespoke feature-based techniques and deep learning-based ones.

Tanvi Goswami et al [2] illustrates many old classical methodologies for skin cancer categorization. According to this survey article, Deep learning CNN-based models outperform typical classical machine learning techniques, such as colour histograms. As a result, this is the first step toward employing deep learning models to classify images.

One of the procedures in survey articles was to first report on how an image classifier CNN can obtain performance comparable to 21 certified famous dermatologists for identifying lesions of malignant . This 3-way method of disease partition was created to determine if a particular skin lesion is benign,malignant , or non-neoplastic. Nine-way partition of disease was also done to classify a particular lesion into any of the 9 categories specified.The cutting-edge InceptionV3 CNN architecture is utilised for skin cancer classification, and the researchers determined that if trained with adequate data, the CNN can beat human specialists. Also, as previously said, if taught with adequate data, CNN may surpass human expertise. Author Zhang also classified four illnesses using InceptionV3 architecture with a modified final layer. The model has been trained on 2 dermoscopic data sets that were almost identical.

Other machine learning models were explored in the survey article. MLP,AdaBoost, NaiveBayes and J48 are a few examples. When compared to other classifiers, the MLP classifier outperformed the others. It was discovered that deep learning models performed better. Misclassification is a significant difficulty when many disease lesions are seen on a single skin scan.

To compare the models, deep learning models with 5 stages, 3 stages, and 2 stages were utilised. The authors solved the class imbalance issue by using an image augmentation approach to balance the category classes.

For skin illnesses, classic approaches need proper feature extraction as well as a segmentation method. Furthermore, since the categorization typically relies on the characteristics chosen, it is critical to identify the essential traits and remove the unnecessary ones. As a result, if irrelevant characteristics are chosen, misclassification may occur. However, unlike CNN, the classical technique does not need a big data set. It effectively picks filters as opposed to the conventional manner of picking filters in the normal approach of extracting important information from photos. As a result, no feature extraction technique is required in the CNN-based approach. However, one can use already pretrained models to classify skin diseases, but they are intensive in terms of resources . Skin is the biggest organ in the human body. It is vital to the preservation of health and life. It assists in the formation of an air tight, waterproof, and adaptable barrier among inner organs and dangerous elements from the exterior environment. Skin diseases account for 1.79% of the global disease burden. The advancement of procedures for visually inspecting a skin illness is critical for expediting diagnosis and minimising life-threatening circumstances. The use of other machine learning techniques with image processing automate the categorization of skin problems has been suggested in the literature. Earlier research has shown that CNNs can recognise particular areas in pictures without the bounding boxes of the annotated specific regions. As a result, for skin classification tasks, this study intends to compare a custom CNN model with the Residual Attention Network model with a custom CNN model based on ResNet without any other attention layers. The attention layer would enhance a CNN model's localization capabilities by considering just the relevant portions of the pictures. Furthermore, the residual network is more effective for small sample learning issues. As a result, a mix of residual and attention units is appropriate for addressing the issues at hand.

According to the research paper by Mehul Jain et. al [3], the Custom Resnet model with the Residual Attention Network increased accuracy to 91 from 86. The above study demonstrated categorization on three levels. Putting an attention component to the residual network helps solve the most major issue in skin illness classification, namely the unpredictability and inclusion of non relevant factors such as clothing, hair, backdrop, and so on in skin disease dataset. The added module of attention assists in concentrating on key elements and eliminating unwanted noise in these photographs. The Residual Attention Network model performed better when compared to custom updated Resnet model.

This model has produced 92.68% accuracy in the task of categorising actual skin sickness photographs received from the domain of Dermnet, according to the paper. This model improved Recall scores, suggesting that real positives were appropriately predicted. This is particularly critical as failing to identify a person with a skin ailment is more harmful than mistakenly categorising a normal individual with a skin illness. The paper's next objective is to expand the aforementioned residual attention network to categorise other skin condition classifications. Improved and revised datasets may aid in the consistency of the models utilised. Because a certain skin illness might impact multiple body regions, having a bigger dataset available can assist produce better outcomes by training models with required data taken from every part of body.

Given the necessity of earlier detection of different diseases, categorization of dermatoscopic pictures has arisen as an exciting field of research. Because of its complexity, dermatology is one of the most surprising and difficult sciences to treat. According to previous studies and findings, the customized model produced results efficient to existing neural networks that employ the dermnet to cure lesions of skin . Data augmentation is applied to build a more effective classifier, which boosts the system's performance. This study has the potential to assist dermatologists make more accurate clinical decisions.

The research paper by Gomathi S [4] provides a bespoke Resnet model of 48 convoluted neural networks with a 95 accuracy. The architecture of the aforementioned model is shown below. Following training, the output accuracy achieved is 95%. According to the research, the custom model's training data set may be greatly expanded to accomplish this. The custom model with the introduction of a dropouts and dense boosted training accuracy from 92% in a ResNet50 model to 95%. In addition, the training loss has been cut from 0.167 to 0.017. The modified ResNet model likewise performs well in contrast to the CNN model, which boosts accuracy by 5% and gives correct results. The model is deployed into a website in order to collect the user's picture of skin illness and predict the type of skin disease.

Skin problems have been on the rise in recent decades. Most of these diseases spread from individual to individual and are also based on visual viewpoints; dermatological illnesses of one portion on a portion of the body may view completely differ on other portion of the body. As a result, it needs to be managed early in order to avoid it by spreading.The suggested approach is broken into two parts: image processing and transfer learning . The transfer learning section is centred with feature extraction and fine tweaking of the pre-trained VGG16 model. When tested on those datasets, the validation accuracy was determined to be 74.1 and, after further fine tuning, it was revealed to be 76.3%. Further training picture data may be utilised to enhance accuracy even further.

The fine tweaking of the vgg 16 model by Srijana Bhusal et.al [5] on imagenet utilising big covnet increased recall accuracy from 76 to 78 using 10 classes of Dermnet. According to the paper, the suggested Residual Attention Network may be expanded to categorise other skin condition classifications. Improved and revised datasets may aid in the consistency of the models utilised. Because a particular skin ailment could damage many body locations, having a larger dataset accessible might aid generate better results by training models using essential data for each area of the body.According to the paper, they obtained an accuracy of more than 76% alongside different assessment matrices such as F1-Score ,recall ,precision and performed a comparative study on the model that was adjusted to train our data, and discovered that the skin's lesion morphology, skin pigmentation, alignment, and the utilisation of data augmentation produce distinct outcomes. Although the model attained accuracy ranging from 74% to above 76%, neurons are still a long way from effectively grasping illnesses since medical diagnosis is a very sensitive instance.

The paper also mentions the issue with the dermnet dataset, which contains Dermnet watermarks and is structured wrongly. Engaging with dermatologists and working with them on naming and right nomenclature will most likely be useful.

Skin provides the most effective barrier for essential human body's organs. It functions as a protection to safeguard our inside organs from harm. Nevertheless, this vital organ of the human may be impacted by deadly infections caused by viruses, fungus or dust. Millions of folks worldwide suffer from numerous skin issues. People suffer terribly from acne to eczema. Some skin illnesses are so infectious that one person may infect another just by shaking hands or using a handkerchief. A proper diagnosis may lead to appropriate therapy, which may alleviate the misery of persons who are suffering and enhance awareness. This study attempted to create a model for diagnosing skin problems using neural networks.By using this methodology on the dermnet dataset of 500 images of different illnesses, we achieved 73% accuracy. This will be a huge accomplishment if the other improvements are completed using a larger portion of the dataset.

Using 32 layer CNN, that was proposed by Tanzina Afroz Rimi et. al , study on dermnet of 5 classes [6] claims accuracy 0.69. The 32 layer is depicted below. The very first layer comprises 32-3 3 filters and a 'linear' activation function. The next layer comprises 64-3 3 filters with the activation function 'linear'. The next layer comprises 128-3 3 filters with the activation function 'linear'. The final layer comprises 256-3 3 filters with the activation function 'linear'.

4 max-pooling levels with a dimension of 2 X 2 are added at the end. At the end, two dropouts layers with parameters 0.3 and 0.4 are added. In the model displayed, there is a levelling layer. Lastly, there are layer capabilities known as softmax and straight of two very different size are employed for commencing work. Softmax computes the likelihood of our five classes.

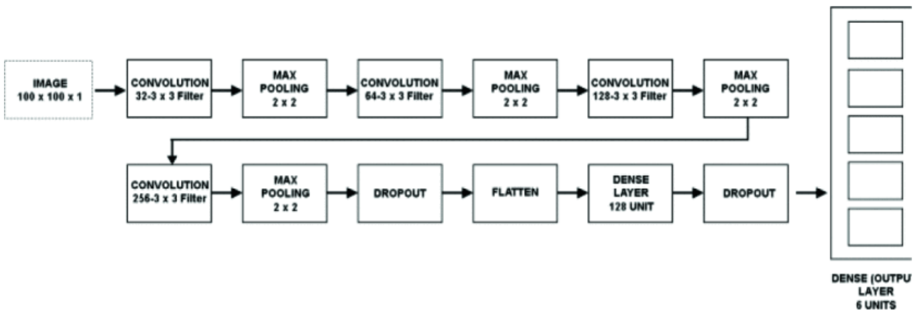


Figure 2.1: Custom Resnet architecture[10]

Cancer is the world's second major cause of death. Skin cancer is a crucial sort of cancer that has been rapidly growing in recent decades. UV rays ,DNA mutations ,smoke and bad lifse style are the main reasons for skin cancers. Clinical screening, dermoscopic analysis, histological study, and a biopsy are utilised to discover this. Early identification of skin cancer may benefit in the treatment of the illness, yet even expert dermatologists find it difficult to identify and classify skin cancer at this stage. Deep learning and transfer learning are shown effective in medical diagnosis. In this paper,it provide a deep learning-based technique for identifying skin cancer. The pre-trained MobileNet convolution neural network was adjusted and trained using the HAM1000 skin lesion data set. This transfer learning technique produced good category accuracy, with recall and weighted average precision of 0.97, 0.91, and 0.90, respectively. This is very lightweight model and produces quick results.

Hasin Younis Muhammad et. al in paper purposed by eliminating 5 end layers of mobilnet from the most recognised low weight model, Ham 10000 delivers weighted average precision [7]. In the study, scientists detected seven kinds of skin cancer with great accuracy using a pre-trained MobileNet convolutional neural network. Actinic keratoses/disease Bowen's (akiec), basal cell carcinoma (bcc), benign keratosis like lesion (bkl), dermatofibroma (df), melanoma (mel), vascular lesion (vasc), and melanocytic nevi were explored in the HAM1000 skin lesion dataset (nv) (nv). The model has a 97 percent categorical accuracy and weighted average precision and recall of 0.90 and 0.91, respectively. MobileNet is a model that is compact, quick, robust, and accurate. Mobilenet can produce results very quickly 2-3 seconds.

Because of variability in spreading length and colour, various skin lesions may look different to the naked eye. This observation, however, is insufficient for adequately identifying illnesses. Dermoscopy was once used to detect skin lesions. It was, however, time-consuming. However, at the turn of the century, Artificial Neural Network (ANN) was commonly employed to construct medical data solutions as it was quicker and simpler. However, ANN was proved to be an inefficient strategy thanks to a paucity of hardware units [3]. Convolutional Neural Networks have had a substantial influence on health data and information processing, where imaging data is better suitable than artificial neural networks. Several prior research on the early diagnosis of skin lesions have demonstrated outstanding outcomes. The purpose of this study is to better characterise 7 distinct skin lesions leveraging the DenseNet-121 architectural mode.

Mehera Binte Mizan et. al has proposed that the Densenet 121 model provided average Precision (0.95, 0.64, 0.74, 0.81, 0.77, 0.92, 0.80, 0.91,) Recall (0.97, 0.41, 0.71, 0.83, 0.65, 1.00, 0.67, 0.91) F1-score (0.96, 0.50, 0.72, 0.82, 0.71, 0.96, 0.73, 0.91) metrics on HAM 100000 [8]. The densenet 121 model is illustrated below with a growth rate of 4. The imbalanced class balance is one of the most major faults with the HAM10000 dataset. No other class comes close to Melanocytic nevi(nv), which contains 6705 photos. The research presents data augmentation ways to address this challenge. It will also help us minimise overfitting. Data enhancement functions such as images rotation and random nonlinear deformation are available. Data augmentation has demonstrated to be highly beneficial in boosting accuracy across a broad variety of scenarios. .For data augmentation, the parameters vertical flipping , rotation range, horizontal flipping, zoom, height and width shift ranges were used.

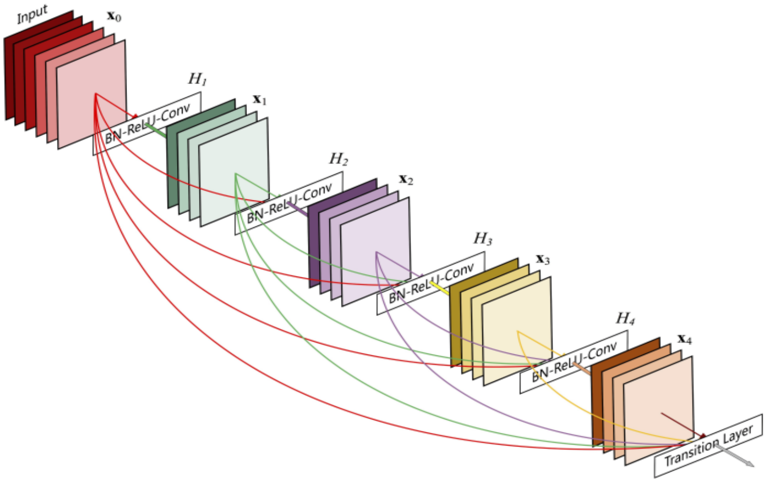


Figure 2.2: Densenet Custom [2]

Due to its complexity, dermatology is one of the most shocking and challenging diagnoses. In the area of dermatology, several tests are routinely conducted in order to detect the skin disorder that the patient may be suffering. The time might differ depending on the practitioner. This is also based on that person's experience. As a consequence, a system that can recognise skin problems without these constraints is necessary. Using machine learning classification, this paper present an automatic image-based technique for detecting skin problems. This system will employ computer algorithms to analyse, process, and relegate image data depending on distinct visual criteria. Skin photographs are filtered to eliminate undesired noise and then processed for image enhancement. Extraction of features utilising complicated methods such as CNN, classification of the picture using the soft max classifier algorithm, and production of the diagnostic report This system will offer more accuracy and provide outcomes quicker than the old approach, making this application an effective and reliable solution for dermatological illness identification. Moreover, this may be exploited as a credible real-time style of teaching for dermatological students.

Another customised CNN model by Jainesh Rathod et. al [9] reveals that the average accuracy attained with 5 classes was 70%. The ReLU, is a non-linear operation. ReLU functions at the most basic level. It is a per-pixel method which multiplies all non-positive values of each pixel in the feature space by zero. It is, in essence, a smooth approximation.

Spatial Pooling, also termed as sub sampling or down sampling, decreases the size of each feature map while maintaining the most significant information on the map. After pooling, the given 3 Dimensional feature map is eventually turned to a 1-dimensional feature vector.

Skin cancer is most common kind of human cancer, and it is usually identified visually, beginning with a clinical screening and progressing via examination of dermoscope, histologic evaluation, and a sample. Because of the fine-grained differences in the views of skin lesions, automatic categorization using images is difficult. Deep convolutional neural networks (CNNs) are used to perform very well for object classification.

Based on a novel regularizer technique, this paper construct a new prediction model which characterizes skin lesions as benign or malignant. As an outcome, this is a binary classifier that differentiates between benign and malignant tumours. The suggested model gained an average accuracy of 97.49%, highlighting its superiority over other cutting-edge techniques. On a range of use cases, the effectiveness of CNN in terms of AUC-ROC with an integrated novel regularizer is tested. The area under the curve (AUC) for nevus vs melanoma lesion, seborrheic keratosis vs basal cell carcinoma lesion, seborrheic keratosis vs melanoma lesion, and solar lentigo against melanoma lesion, respectively, is 0.77, 0.93, 0.85, and 0.86. The results shown to be performing better than previous existing models.

Marwan Ali Albahar et. al proposed a custom regulariser function paired with traditional CNN provided a comparative area under curve of 0.77 for Nevus versus Melanoma. Basal and Squamour 0.93 cell carcinoma versus Seborrheic Keratosis [10] Seborrheic Keratosis vs Melanoma 0.85 Solar Lentigo vs Melanoma 0.76 Regularization is a strategy for controlling the classifier complexity. There are various approaches of doing this task, such as employing dropout in neural networks or L1 and L2 regularizers. They provided an unique novel regularizer based on the standard deviation of the classifier's weight matrix in this paper. In other words, we manage the classifier's complexity by penalising the dispersion of the weight matrix values. As a result, the weights values will be highly related, and will analyse the correlation of these values. The recommended regularizer's mathematical formulation is as follows:

$$\lambda \sum_{i=1}^{k} \sigma(w_i)$$

The regularisation parameter λ penalises the weight. preventing the matrix from accumulating big and dispersed values The number is k represents number of filters in convolutional layer, n represents the number of filters in a convolutional layer parameters in a single convolution filter that are affected by the filter's dimension In Figure 2, for example, in the first There are 32 filters in the convolutional layer, and each filter is of size 3×3. As a result, k =32 and n = 9. where σ is the standard deviation, as seen below:

$$\sigma(w) = \sqrt{\frac{1}{k}\left(\sum_{i=1}^{k} w_i^2 - \frac{1}{n}(\sum_{i=1}^{n} w_i)^2\right)}$$

Human expert skin disease diagnosis is a time-consuming and subjective task. It is potential to improve the effectiveness and robustness of skin disease categorization applying computer technology and machine learning. Deep transfer learning utilising commercially available deep convolutional neural networks (CNNs) shows significant promise for automating skin disease categorization operations. Sophisticated designs, on the other hand, tend to be too hefty for just some few skin disease groups. This research evaluates several parameters in order to uncover future ways for boosting the categorization accuracy of skin conditions. First, two commercially available designs are evaluated: AlexNet and ResNet50. The strategies are then contrasted, with either transfer learning or training from the ground up employed. In order to decrease network complexity, the effects of reducing the depth of deep CNNs are investigated. Moreover, many data augmentation approaches based on basic image change are compared. Finally, the size of the mini-batch is studied. The investigations make use of the HAM10000 skin disease dataset. According on the findings, the ResNet50-based model wins the AlexNet-based model. The transmitted knowledge offered by the ImageNet database adds to the model's accuracy. The decrease in steps in the ResNet50-based model may reduce complexity while keeping accuracy. Furthermore, the use of various kinds of data augmentation techniques, as well as the selection of mini-batch size, may vary the accuracy of skin disease classification.

The survey document by Jiayi Fan et. al [1] concludes that the utilisation of complete off-the-shelf networks feels too complex and is not necessary. The ResNet50-based model outperforms the AlexNet-based model significantly. The model built from scratch is significantly less accurate than the model learned via transfer learning and pretrained on the huge ImageNet database. The depths of the networks were reduced to decrease the complexity of the models, and the two-stage model outperforms the three-stage and four-stage models in terms of accuracy. Choosing the mini-batch size can also assist improve accuracy. .

Table 2.1: Literature Survey

AUTHOR	YEAR	DATASET	TECHNIQUE	Result
Tanvi Goswami; Vipul K. Dabhi;	2020	Dermnet,HAM 10000	Deeplearning and Classical Machine Learning methods	Paper relates the importance of dermoscopic images vs clinical images,traditional color histogram methods vs cnn.
Mehul Jain Kajal Gupta	2022	Dermnet (dermoscopic) 3 classes	Custom Resnet model+Residual Attention Network	Improved Accuracy from 86 to 91
Gomathi S Nishanth S	2022	Dermnet (non watermark clinic) (23 classes)	Custom Resnet 48 - Convoluted Layers 1 - MaxPool 1 - dense	ACC: T: 0.954 V: 0.944 LOSS: T: 0.017 V: 0.037
Anil Kumar Sah; Srijana Bhusal; Sunidhi Amatya;	2019	Dermnet (dermofit 10 classes)	Custom Resnet model	Improved recall precision before and after fine tuning From 76 to 78
Tanzina Afroz Rimi Nishat Sultana	2020	Dermnet(5 classes)	32-3 $\times$ 3 filters and 'linear' as an activation function..	Precision=0.7

Table 2.2: Literature Survey(Contd..)

AUTHOR	YEAR	DATASET	TECHNIQUE	ACCURACY
Marwan Ali Albahar ,Mohammad Wasim	2019	Hamnet 10000	Custom Regulariser function with Resnet	Area under curve Nevus vs Melanoma 0.77 Seborrheic Keratosis vs Basal and Squamour 0.93 cell carcinoma Seborrheic Keratosis vs Melanoma 0.85 Solar Lentigo vs Melanoma 0.76
Jiayi Fan ,Jongwook Kim ,Insu Jung , and Yongkeun Lee , (survery paper)	2019	Hamnet 1000	Off the shelf network models Alexnet, Resnet, VGG	The ResNet50-based model largely outperforms the AlexNet-based model.

Table 2.3: Literature Survey(Contd..)

AUTHOR	YEAR	DATASET	TECHNIQUE	ACCURACY
Haseeb Younis; Muhammad Hamza Bhatti; Muhammad Azeem	2019	Hamnet 10000	Removing 5 end layers from 93 mobilenet layers	Classes Precision akeic 50, bee 55, bkl 77, df 20, mel 28, nv 97, vasc 77, Weight Average 0.90
Syed Rahat Hassan; Shyla Afroge; Mehera Binte Mizan	2020	Hamnet 10000	Densenet-1 by removing 5 end layers of mobilnet[1].21	Average Precision (0.95 0.64 0.74 0.81 0.77 0.92 0.80 0.91) Recall (0.97 0.41 0.71 0.83 0.65 1.00 0.67 0.91) F1-score (0.96 0.50 0.72 0.82 0.71 0.96 0.73 0.91)
Jainesh Rathod; Vishal Waghmode; Aniruddh Sodha; Praseniit	2018	Hamnet 10000	Densenet-121	Average accuracy is 70% with 5 classes

2 Research Gaps

It is observed that light weight models like mobilenet and their variants are giving good accuracies over other standard models. Light weight models are having less no of parameters and easy to train and test with in less time. Very less research has been done on light weight models like squeezenet and varients.

Because of augmentation no of parameters in deep learning model will be grown up rapidly which results in taking lot of RAM and more time to train. In order to avoid imbalance there are several other techniques like changing loss function,giving different ratios to weights while training. This will reduce the no of parameters.

There has not been any standard resizing scale of image proposed to get good accuracy. Most papers are following 224*224. Some images are having small noise like hair on images. Though this wont much affect accuracy, pre processing can be done to remove this noise.

3 Problem Statement

Design and develop an efficient light weight custom CNN model that can classify a skin cancer image.

3.1 Description

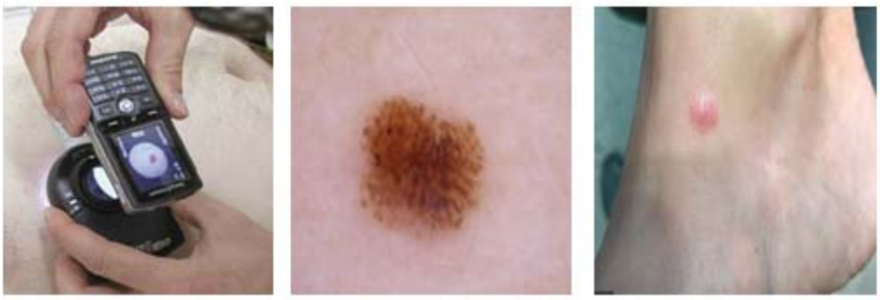
Most research is been observed on heavy deep learning models. These models are heavy because images are augmented to produce equal frequency of each class. To avoid large number of parameters either one has to use models which have less no of parameters or use some other techniques that can substitute augmentation . Models like Squeezenet, Squeezenext, shufflenet, amoebanet etc. are having parameters less than 5 million and they have given better results on imagenet dataset. This project aims to use the ideas of the above light models and implement on this dataset.

Chapter 3

Dataset

1 Clinical and Dermoscopic Images

Clinical image is one that displays the injured physical part of sufferer, such as a wound or a skin problem, or it may be a diagnosis image. The photo was acquired using a digital or convential camera. This kind of image might have different quality,lighting and perspective depending on the camera tha we use to shoot images. Dermoscopic photos are more effective for computer-aided diagnosis. These photographs were shot using a dermoscope, which is a tool used by dermatologists to evaluate skin lesions. The dermoscope generally has better contrast and consistent light. Because of the device's intense light, the lesions are visible and identifiable. Furthermore, because the photographs have less noise, they are simpler to process. Fig.2.1 (a) depicts how to obtain a dermoscopic picture, (b) displays the image under dermoscope, and (c) displays the usual clinical image.



(a) (b) (c)

Figure 3.1: (a).Clinical (b).Dermoscope (c).Clinical [1]

2 Ham 10000 Data set

The HAM10000 dataset is a dermoscopic dataset, which suggests that photos were acquired with a dermoscope. As a consequence, image sharpness will be outstanding. This

HAM 10000 dataset comprises seven distinct types of classes. HAM10000 is a training dataset of 10,000 pictures for recognising pigmented skin lesions. The authors acquired dermatoscopic photos from diverse populations that were obtained and maintained using various modalities.

It is also known as Skin Cancer MNIST. The final dataset comprises 10,015 dermatoscopic photos that have been provided as a training set for machine learning and are freely found via the ISIC repository. This dataset is benchmark dataset used for machine learning and comparing outcomes to human knowledge. Cases give a cross-section of all main diagnostic criteria in the area of pigmented lesions. Pathology verified more than half of the lesions, whilst the balance of the cases depended on the following-up, expert unanimity, or affirmation by confocal microscopy.

Each class of HAM10000 dataset have the following number if images.The dataset is highly imbalanced when we compare the no of images between respective classes. To improve accuracy one has to do required augmentation for the imbalanced classes.

Table 3.1: No of images in each class

S.No.	Class Name	No of Images
1	Melanocytic nevi (nv)	6705
2	Melanoma (mel)	1113
3	Benign keratosis-like lesions (bkl)	1099
4	Basal cell carcinoma (bcc	514
5	Actinic keratoses (akiec)	327
6	Vascular lesions (vasc)	142
7	Dermatofibroma (df)	115

3 Dermnet

The Dermnet data collection is kept by a New Zealand health business. The pics are from http://www.dermnet .com/dermatology-picture-skin-disease-pictures. There are roughly 19,500 photographs in all, with around 15,500 in the train set and the remaining in that of test set. The photographs are in JPEG format and feature three channels, namely RGB. The resolutions fluctuate from picture to image and category to category, but they are not exceptionally good quality photographs. Acne, melanoma, Poison Ivy, Psoriasis, Vascular Tumors, Seborrheic Keratoses, Bullous disease,Eczema, Tinea Ringworm and others are among the categories. DermNet NZ has developed to become a world-renowned skin resource. This data set is held by a health business in New Zealand.

This data set is a clinical data set. The free version of this data set features watermarks, which may be a barrier to training. Before training the data set, web scraping or photo cleaning is neces- sary. The commercial version of this data set is now unavailable while the business adds additional pictures to the collection. However, numerous papers categorised utilising a publicly available public data collection. Many articles have not done 21 class catego- rization as this dataset is too huge. The bulk of these publications basically grabbed a couple of the most prevalent active skin disease photographs and classed them. As a consequence, the papers have a broad range of accuracies.

Chapter 4

Proposed Methodology

1 Architecture

1.1 VGG 16

The input to the network is an image of dimensions (224, 224, 3). The first two layers have 64 channels of a 3*3 filter size and the same padding. Then after a max pool layer of stride (2, 2), two layers have convolution layers of 128 filter size and filter size (3, 3). This is followed by a max-pooling layer of stride (2, 2) which is the same as the previous layer. Then there are 2 convolution layers of filter size (3, 3) and 256 filters. After that, there are 2 sets of 3 convolution layers and a max pool layer. Each has 512 filters of (3, 3) size with the same padding. This image is then passed to the stack of two convolution layers. In these convolution and max-pooling layers, the filters we use are of the size 3*3 instead of 11*11 in AlexNet and 7*7 in ZF-Net. In some of the layers, it also uses 1*1 pixel which is used to manipulate the number of input channels. There is a padding of 1-pixel (same padding) done after each convolution layer to prevent the spatial feature of the image.

After the stack of convolution and max-pooling layer, we got a (7, 7, 512) feature map. In next layer, flatten this output to make it a (1, 25088) feature vector. After this there is 3 fully connected layer, the first layer takes input from the last feature vector and outputs a (1, 4096) vector, the second layer also outputs a vector of size (1, 4096) but the third layer output a 1000 channels for 1000 classes of ILSVRC challenge i.e. 3rd fully connected layer is used to implement soft max function to classify 1000 classes. All the hidden layers use ReLU as its activation function. ReLU is more computationally efficient because it results in faster learning and it also decreases the likelihood of vanishing gradient problems.

1.2 Mobilenet

The MobileNet model is designed to be used in mobile applications, and it is TensorFlow's first mobile computer vision model.

MobileNet uses depth wise separable convolutions. It significantly reduces the number

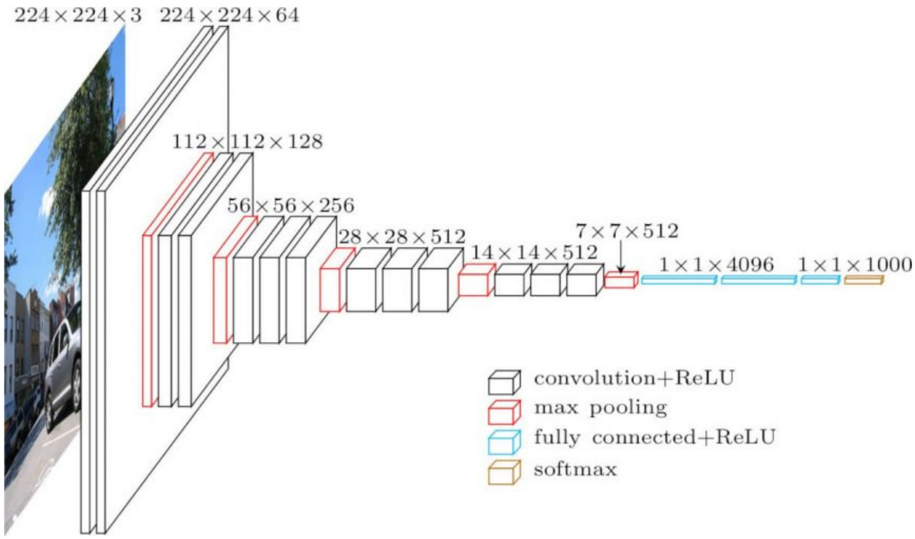


Figure 4.1: VGG-16 Architecture

of parameters when compared to the network with regular convolutions with the same depth in the nets. This results in lightweight deep neural networks.

A depth wise separable convolution is made from two operations.

1. Depth wise convolution.

In a normal convolution, all channels of a kernel are used to produce a feature map. In a depthwise convolution, each channel of a kernel is used to produce a feature map.

2. Point wise convolution.

To increase the number of channels in output image to 256: In a normal convolution, models just have to use 256 filters of size 5x5x3. In a point wise convolution, mobilenet just have to use 256 filters of size 1x1x3.

MobileNet is a class of CNN that was open-sourced by Google, and therefore, this gives us an excellent starting point for training our classifiers that are insanely small and insanely fast.

Since the research on the light weight models like mobilenet and squeezenet and variants on vgg16 with out augmentation has been less ,its a good challenge to work on. This project aims to work on the light weight variants and vgg 16 variants.

2 Workflow

2.1 Data Preprocessing

Due to imbalance in no of images loss rate will increase and accuracy will be dropped. In order to avoid this we have to balance this data set. There are several techniques to balance data set. Here are some.

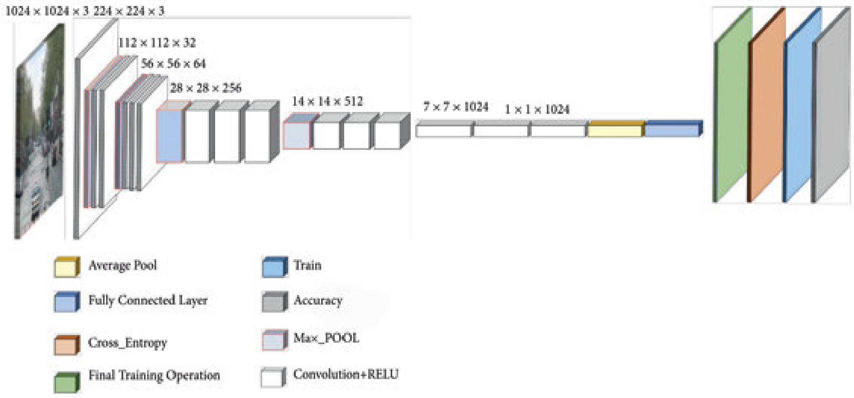


Figure 4.2: Mobilenet Architecture

1.Re Weighting:

Here loss function is influenced by assigning relatively higher costs to examples from minority classes. One can use the re-weighting method from scikit-learn library to estimate class weights for unbalanced data set with 'balanced' as a parameter which the class weights with respect to ratios.

2.Learning Rate Scheduler:

Constant learning rate is the default learning rate schedule in any optimizer. It is tricky to choose the right learning rate in order to get the best optimization in the training phase. By experimenting with a range of learning rates in our example, lr=0.001 shows relatively good performance to start with. This can serve as a baseline for us to experiment with different learning rate strategies. The learning rate scheduler is to make the learning rate of optimizer adapt in a particular situation during the training phase. A learning rate scheduler relies on changes in loss function value to dictate whether the learning rate is decayed or not.

3.Data Augmentation and Re sampling:

One of the basic approaches to deal with the imbalanced data sets is to do data augmentation and re-sampling. There are two types of re-sampling such as under-sampling when we removing the data from the majority class and over-sampling when we adding repetitive data to the minority class.

In this approach, We combine data augmentation and re-sampling technique by applying selective data augmentation to balance the data set by re-sampling less frequent samples to adjust their amount in comparison with predominant samples. Augmentation is done by rotating images.

To balance Ham10000 data set Data augmentation technique is used. Before doing augmentation every image of size 600*450 to 224*224.After resizing data augmentation is performed. Data argumentation techniques include zoom, horizontal flip, height shift range, width shift range, and shear range. As a result, we can train better with a larger amount of training image set. After resizing the images augmentation is performed by rotating

2.2 Training Algorithm

The dataset is divided into train, validation and test splits of size 60%,20%,20%. It is observed that above splits have gained better accuracy. Various standard models have shown the following accuracies.

Table 4.1: Models

S.No.	Model Name	Augmentation	Accuracy
1	Alexnet(Trasnfer Learning)	No	71
2	Alexnet(Scratch)	No	66.4
3	4-stage Resnet50(Transfer Learning)	No	76.4
4	3-stage Resnet50(scratch)	No	64
5	2-stage Resnet	Yes	77
6	Alexnet	No	70
7	Mobilenet	Yes	92

2.3 Performance Evaluation

Accuracy: An overall measure of the model's performance across all classes is called accuracy. When all classes are of similar importance, it is helpful. The percentage of accurate predictions divided by the total number of predictions is used to compute it.

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN}$$

Precision: It can be defined as the ratio of true positives divided by the total number of predicted positives.(i.e., true positives and false positives are summed together).

$$Precision = \frac{TP}{TP + FP}$$

Recall: It can be defined as the ratio of true positives to sum of true positive and false negative.

$$Recall = \frac{TP}{TP + FN}$$

F1 score: It can be defined as the harmonic mean of two evaluation metrics i.e precision and recall.

$$Precision = \frac{2 * precison * recall}{precision + recall}$$

Chapter 5

Conclusion and Future work

Several research papers and survey papers show that Deep learning models perform better than classical machine learning models for skin cancer classification. Since the classes of Ham 10000 data set are imbalanced it becomes challenging to improve accuracy. The dermnet data set which is balanced yet it is challenging to improve accuracy because of the water marks on images. For imbalanced data sets necessary additional data creation required and needed.This can be done by image augmentation. For dermnet data set image denoising should be done for increasing accuracy

There is slight noise on some images of HAM1000. Though this noise would not affect accuracy much removing the noise might improve accuracy. Noise on these images is due to hair present on them.

Since the images are of size 720*650 original images cannot be used for deep learning models as the no of parameters will be quite a big number, standard resizing of 224*224 might make the image to lose the information, there should be some other method of solving these issue in order not to loose the information.

Chipping is a technique that can deal imbalance and also avoid losing important information.Chipping raw images into smaller tiles is an alternative to down sampling. By preserving full resolution, we can ensure that smaller-item minority classes don't become even harder to identify.Each image is tiled into smaller square cells, which can be fed into the network individually while retaining the original image resolution. To ensure that no information is lost for objects split across tile boundaries, one can chip the image with overlap between consecutive tiles (e.g. 25% overlap).

When one use heavy standard deep learning models no of parameters will be huge. If images are not augmented no of parameters of the models can be reduced significantly. Other techniques like adjusting lose function,Re weighting techniques will not add extra images to data set. Thus this can reduce the no of parameters for training while performing with deep learning models.

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