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SKIN CANCER DETECTION USING DEEP LEARNING ALGORITHMS CNN

Aiman Ali Batool
Department of Computer Science, NFC Institute of Engineering and Technology, Multan, Pakistan.
Hasnaib Khan
Computer Science Department Institute of Southern Punjab Multan, Pakistan.
Saima Ali Batool
Department of Computer Science, NFC Institute of Engineering and Technology, Multan, Pakistan.
Mohsin Ali Tariq
Department of Computer Science, NFC Institute of Engineering and Technology, Multan, Pakistan.
Naeem Aslam
Department of Computer Science, NFC Institute of Engineering and Technology, Multan, Pakistan.
Haseeb Ur Rehman*
Computer Science Department Institute of Southern Punjab Multan, Pakistan.

**Corresponding author: Haseeb Ur Rehman (haseeburrehman@isp.edu.pk)*

Article Info

Abstract

Skin cancer is a serious problem that is frequently ignored. Sometimes, when a doctor does a manual examination, the human eye cannot accurately identify illnesses from imaging data. Deep learning techniques are increasingly being used in today's world to solve problems in our daily lives. Thus, we use deep neural network methods to create an automated computerized system for identifying skin conditions. We employed a number of neural network algorithms in the suggested model, analyzed their results, and determined which algorithm performed the best in terms of accuracy in detecting the five main skin conditions. CNN, and we have developed a new model to achieve an accuracy of about 80% by utilizing the Keras Sequential API. Later, to improve accuracy and for comparison, we have employed pre-trained data-based architectures. These deep learning models consist of DENSENET201 andinception-v3. The ResNet architecture achieves the maximum accuracy of 97% among the algorithms employed in the suggested models.

Keywords:

skin cancer; image segmentation; classification; extraction; Convolutional neural network (CNN), Transfer learning, Deep Learning.

1. Introduction

Melanoma is a very common and dangerous form of skin cancer that it is estimated affects millions of people across the world. Early diagnosis has a direct positive correlation with survival statistics, and in this world of technology, Convolutional Neural Networks (CNNs) are by far a great tool that helps in automating this. As you will read in this blog, it is a step-by-step tutorial Convolutional Neural Networks (CNNs) have become a potent ally in automating the process of developing a CNN model for skin cancer diagnosis in this digital age, catering to ML experts, ML novices, and product managers.

For ML experts, ML novices, and product managers, this blog provides a comprehensive road map for building a CNN model for skin cancer diagnosis using the HAM10000 dataset—a collection of less diverse but more accurately curated skin lesion images. Apart from the special features of employing CNNs in designing this network, this guide seeks to establish the potential of such a technology when applied to solving relevant human issues in healthcare – especially dermatology[1]. In 2016, there was a change in terms of the investigation on lesion classification methods.

The techniques presented at the 2016 International Symposium on Biomedical Imaging (ISBI) serve as an example of this shift. Instead of using conventional standard machine learning techniques, the 25 participating teams all used convolutional neural networks (CNNs), a deep learning method [2] .

1.1 Using the Backpropagation Algorithm

Metastasis starts to emerge in the malignant melanoma and the cancer starts to expand to its envoirment. Melanoma is a great risk though if detected early and treated the prognosis is good4. Melanoma diagnosis in its early stages is not only one of the most challenging fields of research in oncology but is also essential. Majority of the cancers fall under the non-melanoma category as seen by the SCC, BCC and SGC. Melanoma cancers are more likely to affect other parts of the body as compared to non-melanoma cancers which are not so responsive and easy to treat. The treatment of skin cancer is effective when the disease is diagnosed in its preliminary stage[3].

Currently there is limited management for skin cancer which means early diagnosis is crucial. The most likely approach for the prevention of skin cancer will require two components: proper evaluation and the capacity to identify skin cancer. For coupled unsupervised literacy Deep literacy has been used significantly ,as mentioned earlier [4].

such technologies, the CNNs outperded knowledgeable specialist in classifying the lesion concerning skin cancer, during the last couple of years[4]Single frame recognition is least erroneous, with Inception-v3 network having top-1 error bar of 3HD21.2% and top-5 error bar of 5HC5.6%, showing remarkable improvement over the current standard. These improvements were highlighted when using the validation set of the 2012 ILSVRC classification task. Hence the following end-to-end model; this model is trained using RMSprop in several GPUs

1.2 Back Ground

In 2019, there were approximately 96,480 new cases of melanoma diagnosed in the US. and approximately 7230 deaths resulted from this3. One of the causes of skin cancer is UV radiation that results from sun exposure3. It invades surrounding tissues in late stages or malignant melanoma. But nevertheless, melanoma is among severe sorts of cancer, and even if it appears that the risk is high, the probability of the disease's recovery if it is discovered at an initial stage is high4. Early-stage melanoma diagnosis is not only one of the most challenging areas of study, it is also one of the most important.

Most of the cancer incidences; therefore, fall under the non-melanoma type of cancer such as SCC, BCC, and SGC. Usually non melanoma cancers are not invasive and can easily be treated compared to the melanoma cancers. It is also important when diagnosing skin cancer Indeed, according to the statistical data of 2019, there were around 96,480 melanoma cases in the US, and roughly 7230 people died from it. Sunbathing and exposure to the UV light is the causes of skin cancer, usually only contracted at an early age4.

1.3 Convolutional Neural Network(CNN) Implementation On TensorFlow Concept

Fully Connected Neural networks' performance have been surpassed for tasks like object detection and bracketing by Convolutional Neural Networks (CNN's). CNNs overcome the requirement for people to develop feature sets because CNNs are trained entirely in a supervised manner. Among. To fine tune the Inception-v3 network and change its weights Mel NET uses backpropagation of forecasted errors[6]. The human body has a lot of changes as much as skin cancer has changes in its symptoms. There is a lightening of the skin tone, the mole's size increases, and now wood has ulcers. These symptoms however can vary depending on the use.

A tumour or vein becoming visible in a basal cell carcinoma and a swelling smooth platform on the neck and shoulder. Although these tumor arise from bleeding within the tumor center, they are considered fully treated for cancer of this type.

Squamous cell carcinoma is also the skin cancer that looks like hard nodules. Mucus crusting, ulceration and hemorrhage from the tumour may be the result. If this particular kind of cancer is not taken care as early as possible, a large mass appearance on the skin. Merkel skin carcinoma (MCC) cancer start out as a painless red nodule and is hence removed for a cyst[5]The following is a list of characteristics that are considered while making a diagnosis:

Typical pigment spread in conjunction with the lesion's homogeneity or heterogeneity

Shaded areas describe the lesion characteristics and include the following: The fact that skin surface is keratinized The degree of oddity in blood vessels' shape presence of ulceration and burning sensation are the other features found in a patient with diabetes among relatives. Specifications used for the analysis of MRI were the following: irregular border of the lesion. White, gray, black, yellow, or even brown are examples of color [6]

2. Literature Review

This complexity is due to the fact that some attributes of melanoma are hard to define. This challenge is further illustrated in figure 1 where we randomly pictures taken from the ISIC 2017 dataset, which includes both cases of melanoma ("mel") and other skin lesions that are not melanoma ("nomel"). Consequently, some Invalid source specified are qualitatively similar to the specific source employed in the present work. Source is invalid.

More of these images depict the general challenges facing doctors who try to differentiate malignant from benign skin lesions Of all the known genetic and metabolic abnormalities that can lead to cancer-which is often fatal – the number is enormous. There is no limb that cannot be attacked by either cancerous cells at times the results could be fatal. Cancer of skin is among the most prevalent forms of cancer, and its incidence is unfortunately rising globally.

Skin cancer mainly consists of four forms being squamous and basal cell carcinoma, melanomas and other clinically aggressive melanomas that are life threatening and responsible for deaths. The absence of cancer, in particularly skin cancer, is however dependent on early screening[7].

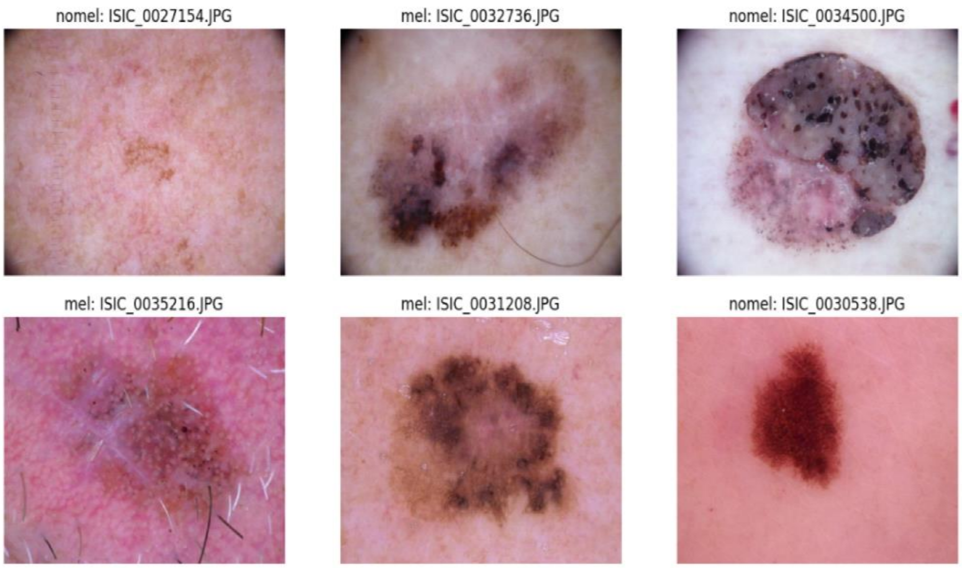

Figure 1 image Form ISIC 2017 Dataset

An improvement in the melanoma diagnosis is dependable on the ABCD rule based systems as well as the computer assisted systems. Often such systems could be divided into the units of categorization, feature extraction, and picture segmentation [8–12]. The following are studies that have been done in this area: Professional judgment and artificial neural networks can be compared in a study made by Baldrick et al. when the lesions are to be classified.

They got from the computerized a 95% sensitivity and 88% specificity in the dermatology program; they then calculated the sensitivity and specificity of the expert dermatologist to be 95% and 90% respectively [13]. Other tries for early detection concerning the skin cancers, using a genetic algorithm with an artificial neural network technique, resulted in sensitivity of 91.67% as well as specificity of 91.43%[8].As for computer aiding this field, prior to the advent of machine learning approaches with regard to Most computer algorithms, including CNNs, tried to use a similar scoring approach and discover the key aspects from the clinical procedures.

Nevertheless, the current use of CNN-based methods in other image processing tasks, such as detection, localization, segmentation, and classification [3]–[5], has also spread to this field as it predicts that machines would outperform human specialists in recognition accuracy.[6][9]Fully automated approaches have in the past been used to address the problem due to the limited availability of the Medical training data set including annotations for skin lesion analysis, segmentation, and classification Techniques that use inference from a dataset to aid in decision-making are applied in unsupervised deep learning approaches [33].

2.2 Review of literature and relevant Research

These techniques often use thresholding, iterative or statistical region merging, or the application of energy functions [31] [34] [35]. Additionally, they employ probabilistic generative models. that can learn the approximate level of hierarchy and the probability density of particular input space for image[10].

Coded images and their interpretation as depicted through dermatologists examining with computer-aided diagnostic (CAD) systems that involve image processing and pattern recognition algorithms. However the automated evaluation of dermoscopy pictures is often affected by artifacts such as specular shadows or black hair concealing the lesions in the skin. Therefore, it can be said that the detection of and subsequent removal of such relics is one of the most important pre-processing phases.

2.3 Generative Adversarial Network (GAN)-based skin cancer detection Technique

In this context, for this assignment, many Researchers have used general noise reduction methods such as median filtering[5] and Gaussian filtering [4] or morphological closure in greyscale [11]GANs method is growing in recent years and being used in a growing number of medical applications, including reconstruction, detection, segmentation, classification, and medical synthetic images [26]. Nevertheless, data augmentation methods based on image synthesis has been conducted only for two years for skin lesion images and there are limited investigations and discussions according to our previous literature review[28,31,34,36,38]. The low resolution of the image is one of the main problems in current research of skin lesion image synthesis through those most utilized methods, such as DCGAN.

There are still higher order architectures of GANs that are capable of generating high resolution images that still has to be applied for skin lesion image synthesis [45] Moreover, deep learning techniques have in recent years been very successful in image and text analysis. It can be classified as a representation learning approach [12] which learns some improved features that could enhance a model generalization capacity. Deep learning for instance is more uninterpretable than the others[12]

3. Materials and Methods:

3.1 Dataset

Big data is rather significant for the tools to understand the complex details of the problem efficiently. Hence to assess The effectiveness of certain diagnostic instruments and more importantly ensure that the network is pulling relevant and diversified data set a feature rich data set is needed. But despite the advances in this area, the small relative number of cancer datasets as well as their heterogeneity have typically restrained the application of artificial networks in cancer studies. Since the amount of existing data cannot be increased any further, artificial intelligence AI networks must generate synthetic data. may have to embrace few-shot learning to counter this weakness and understand the subtleties of different tumor related data. Table 3.1 The crucial datasets employed to establish the AI networks coming with the start of the networks. A brief discussion of the designs based on HAM10000 will be discussed as the main focus of this thesis later in this section.

Table 3.1: Table of Datasets

The Dataset's Name	Year of Publication and Updates	Number of Pictures
DermQuest	1999	22082
AtlasDerm	2000	1024
ISIC archive	2016-2020	25331
Dermnet	1998	23000

HAM10000	2018	10015
DermIS	-	6588
PH [2]	2013	200

3.2 DensNet201

DenseNet201 is a type on Dense Net that uses the creation of dense blocks whereby all the subsequent layers above a given block are connected to it. The high interconnectivity of the network enhances information storage, and the mere fact of the reusability of the features. The forward pass of DenseNet201 can be represented mathematically as follows:

$$x1 = H1([x0, x1, \ldots.., xl - 1]) \qquad (3.3)$$

where (x_1) is the (l)-layer's output, and the composite function of the [x 0 x 1::: x l-1] provides the representation of the feature maps from all previous layers up to (l-1). or (H_l). This design merely allows individual connections between the layers, and makes each layer reusable and with an efficiency and fewer parameters in the network. Many densely connected blocks in DenseNet201 all have a positive impact on the layers that are able to acquire and reconstruct deep hierarchical features when approaching the last layer. The dense convolutional pass for DenseNet201 can be summarized as follows mathematically: Dense Block$k$ = Transition Layer$k$ (Input) (3.4) For instance, the k-the densely connected block in this case is referred to as the Dense Block while Transition Layerk means the layer that Major channel depth reduction for efficiency here. use. The forward pass of DenseNet201 can be represented mathematically as follows:

$$x1 = H1([x0, x1, \ldots.., xl - 1]) \qquad (3.3),$$

where (x_1) is the (l)-layer's output, and the composite function of the [x 0 x 1::: x l-1] provides the representation of the feature maps from all previous layers up to (l-1). or (H_l). This design encourages individual connections between the layers, which promotes feature reuse and optimizes the amount of parameters in the network. Each of DenseNet201's many densely connected blocks contributes positively to the number of layers that can handle and evaluate deep hierarchical characteristics as they progress to the final layer. DenseNet201's entire forward pass can be expressed mathematically as follows:DenseNet201's entire forward pass can be expressed mathematically as follows: Dense Block$k$ = Transition Layer$k$ (Input) For example, the k-the densely connected block in this scenario is called Dense Block while Transition Layerk refers to the transition layer that reduces channel depth for efficiency. The DenseNet201 architecture is optimal for picture classification problems because to its capacity to nab representations across sizes.

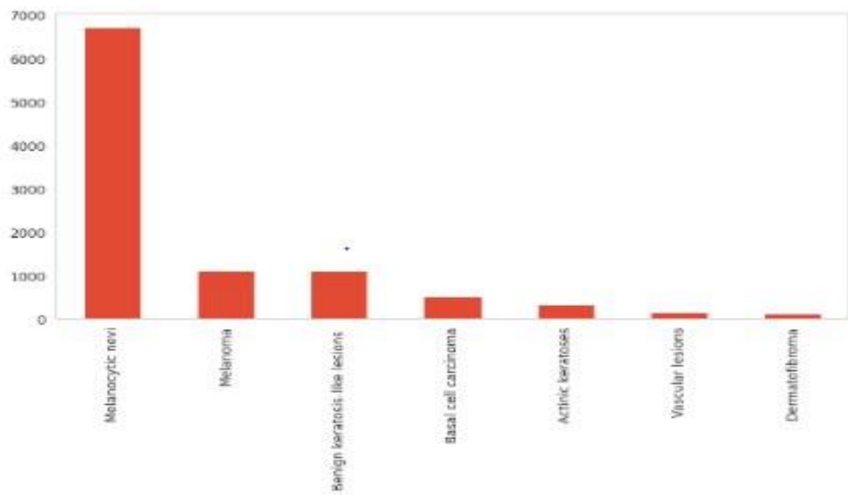

Figure 3.2: Skin cancer differentia table into several types.

3.3 Inception-v3

The Inception-v3 methodology is a deep learning model to assist in image identification by Szegedy et al. in 2015. This model employs, several instances of inception modules; it must be noted that inception modules comprise fully connected, pooling, and convolutional layers. This is the primary inception block where the input signal is handled several paths on the basis of filter size (like 1x1, 3x3, 5x5 etc.) and several feature maps are then concatenated Mathematically, convolutional layer can be described as Y is the output feature map, σ is the activation function (ReLU), W is the weights, X is the input feature map, and b is the bias in the formula $Y = \sigma(W * X + b)$.

3.4Classification of skin cancer

The HAM10000 dataset's skin lesion categorization typically entails categorizing unique skin lesions based on their visual characteristics. After analyzing and reviewing the provided data set, it is feasible to conclude that the data set contains seven different categories of records.

1.Basal Cell Carcinoma (BCC)

- The most prevalent type of skin cancer.
- It develops from basal cells in the epidermis.

2. Squamous Cell Carcinoma (SCC):

- The second most prevalent type.
- Caused by squamous cells on the skin's surface.
- Manifests as a red, scaly area, nodule, or ulcer.

3. Melanoma:

- The most aggressive and lethal form.
- Melanoma originates from melanocytes, which produce melanin (skin pigment).
- Also known as a changing mole or new dark lesion.

4. Merkel Cell Carcinoma (MCC)

- Commonly found on sun-exposed skin, this nodule grows quickly, is firm, and painless.
- High danger of spreading throughout the body.

5. Kaposi Sarcoma

- Develops from the lining of blood and lymphatic vessels.
- Often linked to HIV/AIDS or immunosuppression. .
- Can impact internal organs like the lungs and gastrointestinal tract.

6. Dermatofibrosarcoma Protuberans (DFSP)

- is an uncommon type of skin cancer that starts in the dermis, the deeper layer of the skin.
- The nodule is slow-growing and solid, resembling a bruise or scar.
- Low metastatic potential, but can develop aggressively locally, necessitating extensive resection.

7.Sebaceous Carcinoma

- is a rare and aggressive cancer that affects the skin's sebaceous glands.
- A painless lump or nodule may appear on the eyelids.
- High chance of spreading to neighboring tissues and other areas of the body.

Table 1.2: An overview of the dataset HAM10000.

Type of Skin lesion	**Number of Pictures**
Melanomas	6705
Nevi, the melanocytic	1113
Dermatofibromas	115
Keratoses Actinic	327
Lesion on Vascular Skin	142
Cancer of the basal cell	514
Innocent Keratoses	1099

Results

4.1Setup for an Experiment

The experimentation of the thesis was performed on a laptop inbuilt with Intel Core i5_4310U CPU @ 1.90GHz, 16 GB RAM and 16 GB P100 GPU. The analyses employed the programming language Python 3.6.9 to perform experiments in a Jupyter notebook integrated in Google Colab. Figure 4.1 depicts the whole. The method adopted throughout the experiment that led to formalization of this model to solve the decision making problem of skin cancer identification.

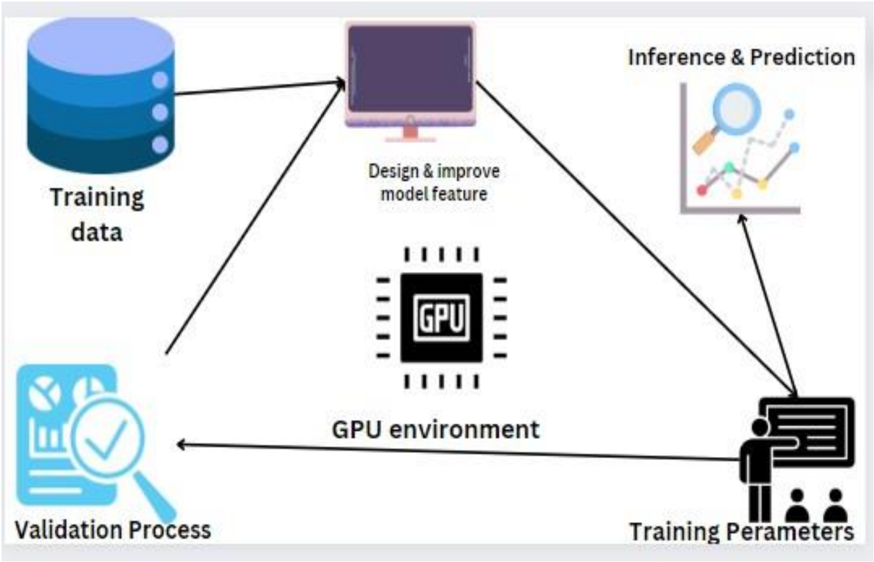

Figure 4. 1: Experimental setup

4.Two software libraries have been made available.

4.1 PyTorch was chosen for the experiment because it has received positive feedback for generating cleaner code and superior computing performance. TensorFlow: Fast CPU A number of early project pilot tests were previously designed using CUML in conjunction with other libraries, including matplotlib, pandas, NumPy, SciPy, and the sci-kit learn toolkit software stack.

4.2 Deployed evaluation metrics

When assessing skin lesion identification using the DenseNet201 and Inception V-3 architectures, the following metrics are used: Verified Positive: TP

False Positive: FP

True Negative: TN

False Negative: FN

Table 2.1: Confusion Matrices

	Predicted Values for Class 1	**Predicted Values for Class 2**
Actual Values for Class 1	True Positive (TP)	False Negative (FN)
Actual Values for Class 2	False Positive (FP)	True Negative (TN)

4.2 Performance Metrics:

- Accuracy
- Precision
- Recall
- F1-score
- ROC-AUC
- Sensitivity

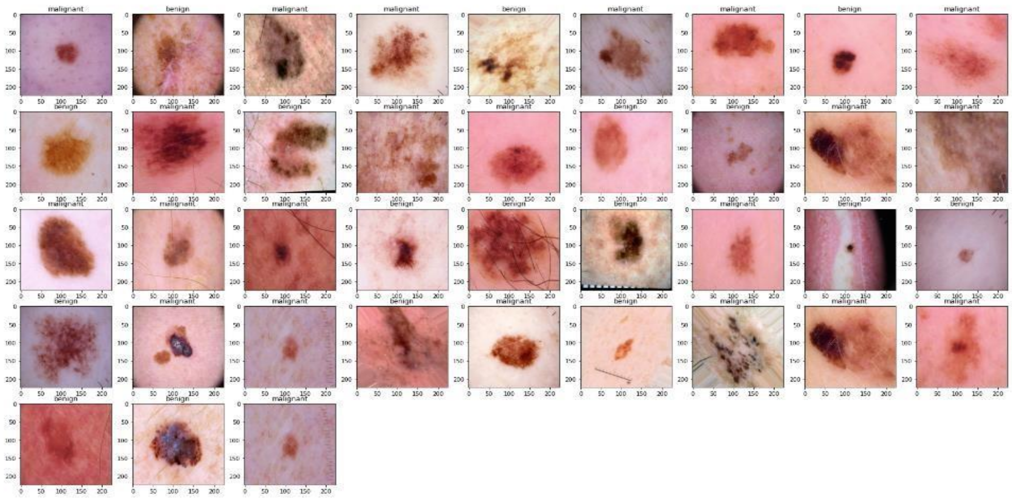

Figure 2 Pictures especially when it comes to visualization.

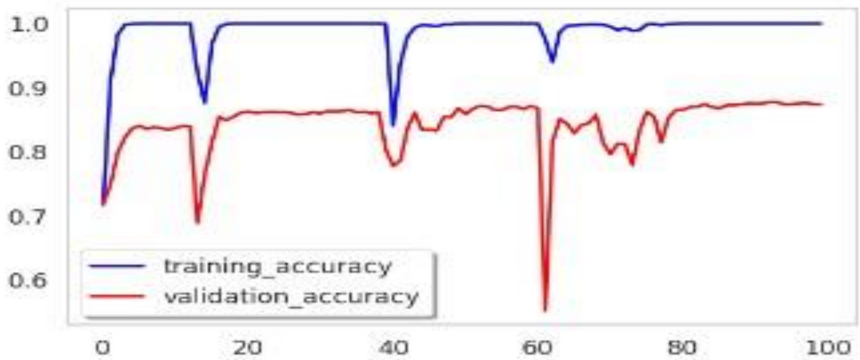

Figure 3Model precision

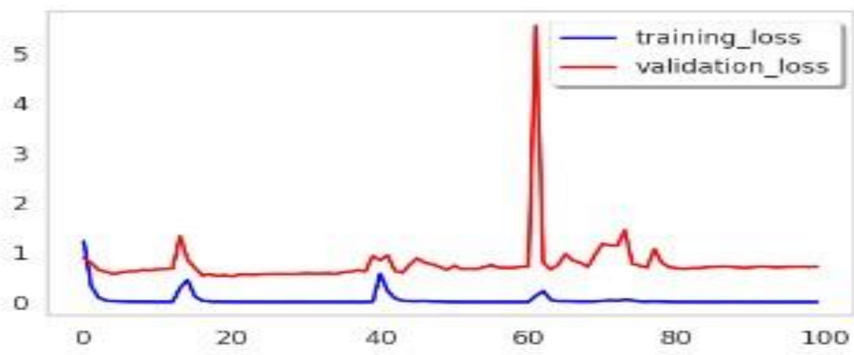

Figure 4 Model depletion

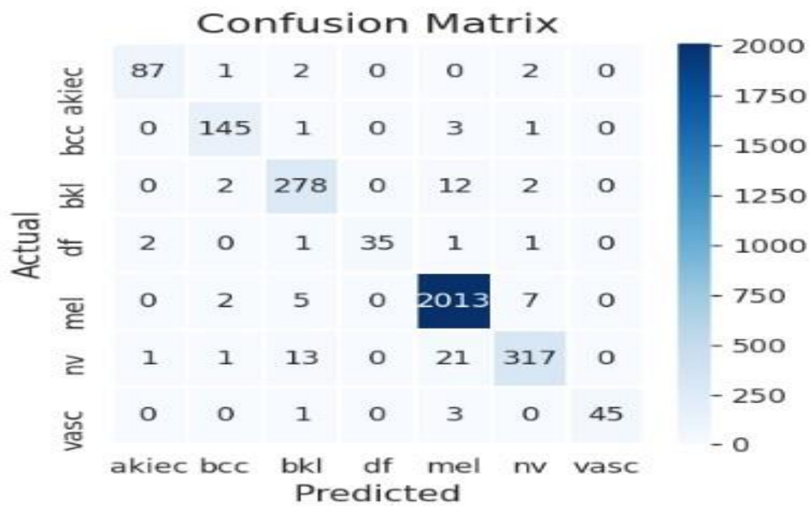

Figure 5 Confusion matrices of DensNet201

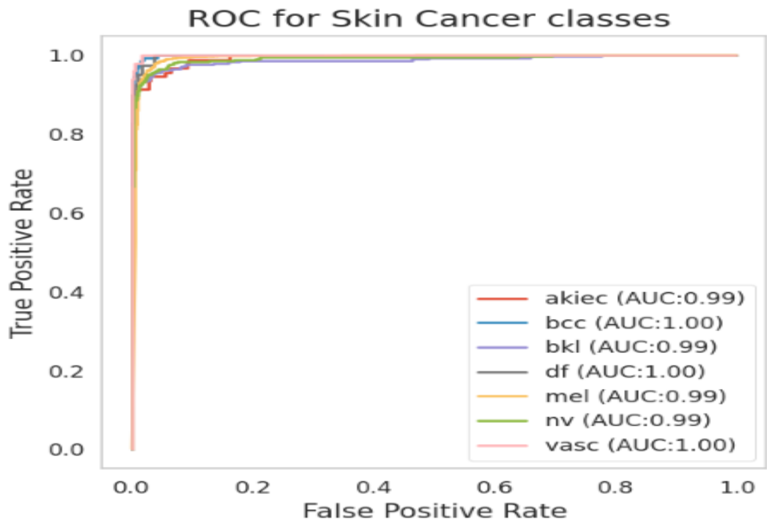

Figure 6 ROC for skin cancer

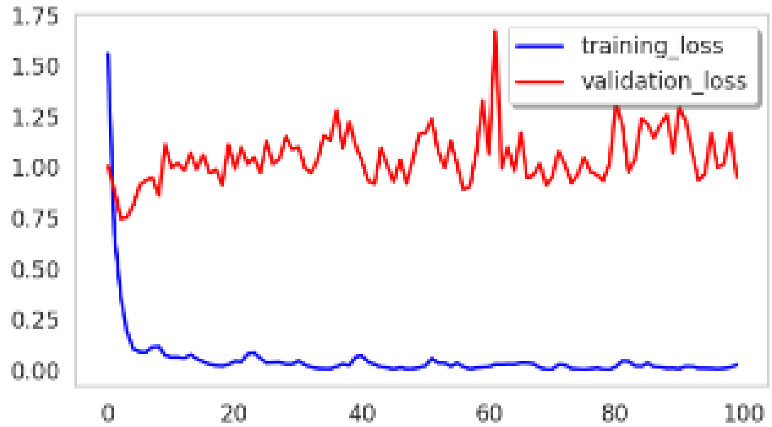

Figure 7 Loss of Model.

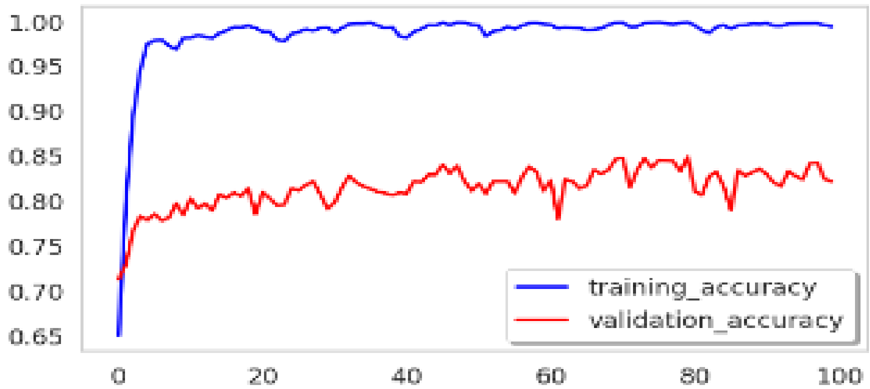

Figure 8 Model Precisions

4.3 Comparison Of InspectionV3 and DensNet201

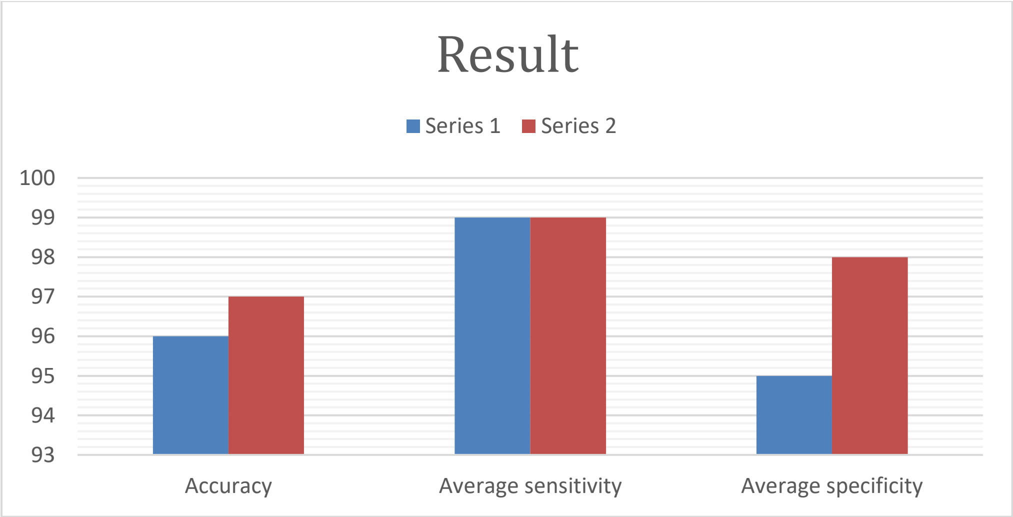

Table 4.2: Continuing from a previous section, the table below compares the performance of different state-of-the-art methods in the classification of seven types of skin lesion from the HAM10000 dataset.

HAM10000 dataset.

Authors	Method		Accuracy
Pai and Giridharan[77]	VGGNet.		Testing accuracy: 0.780
Nugroho et al.[71]	CNN		0.800 for training and 0.780 for testing accuracy
Khan et al[73]	SVM		Testing accuracy: 0.898
Sae-Lim et al[76]	Mobilenet		F-measure: 0.820, recall: 0.850, accuracy: 0.832
Mobinyet al.[75]	DensNet169		Testing accuracy: 0.8359 ± 0.170
Shahin et al[72]	ResNet50 InspectionV3	and	Validation accuracy 0.899.
Moldovan [74]	Dens Net		Level 1 accuracy is 0.850, level 2 accuracy is 0.750.
Proposed	DensNet201		In training, accuracy was 0.974; in validation, it was 0.873.

5 Conclusion

In other words, this thesis introduces a new pipeline, Skin CAN AI, to support dermatologists in making decisions on some critical steps toward skin tumor diagnosis as well as identifying possible malignant skin lesions. Skin CNN mitigates the problem of limited data selection by creating new skin lesion data samples and refining the training parameters of the suggested DenseNet model for skin lesion classification.

Generative adversarial networks have already been attempted to be used by the scientific community, however their high computational resource requirements and instability during training make practical application difficult. However, these issues are resolved by the suggested design because inference and training need a large amount of processing power. The algorithm for effectively gaining knowledge from a limited dataset.

Two transfer learning-based non-Deep afflicted frameworks are used to identify moles in skin cancer. Five additional skin disease types were to be identified in addition to nevi and melanoma classification. For use in the two suggested frameworks, two popular convolutional neural networks were optimized:

Both a basic two-level hierarchical model and a two-level model with an additional level that could distinguish between image of benign and cancerous moles. Both these frameworks were built with the help of the HAM10000. datasets.

5.1 Future work Based current work

The experiments show that DenseNet201 is the most effective deep network overall, surpassing others by about 10%, with attention to recall, which is a decisive factor in reducing the number of false negatives in diagnosis. Even in both binary and in seven-class classifications, the plain model had good performance with nearly a 95% accuracy throughout the HAM10000 dataset.

Nonetheless, despite data augmentation, distortion in the distribution and insufficient image data significantly influenced the DenseNet201 in the second level classifier. Notably, to facilitate a direct comparison of the performances of the deep networks under the same parameter count, the same number of parameters were used for all of them.

Subsequent works will consider further networks and other kinds of hierarchies, and detailed techniques for preprocessing the six categories apart from nevi. Sifting through the features for each class and more generally, creating suitable classifiers, will therefore require a close analysis of the properties of each class; another possibility for future research is to rely on probability estimates to accurately predict the behaviour of a wide range of classifiers.

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