Skin Cancer Detection Using Deep Learning and Artificial Intelligence: Incorporated model of deep features fusion

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Abstract

Among the most frequent forms of cancer, skin cancer accounts for hundreds of thousands of fatalities annually throughout the globe. It shows up as excessive cell proliferation on the skin. The likelihood of a successful recovery is greatly enhanced by an early diagnosis. More than that, it might reduce the need for or the frequency of chemical, radiological, or surgical treatments. As a result, savings on healthcare expenses will be possible. Dermoscopy, which examines the size, form, and color features of skin lesions, is the first step in the process of detecting skin cancer and is followed by sample and lab testing to confirm any suspicious lesions. Deep learning AI has allowed for significant progress in image-based diagnostics in recent years. Deep neural networks known as convolutional neural networks (CNNs or ConvNets) are essentially an extended form of multi-layer perceptrons. In visual imaging challenges, CNNs have shown the best accuracy. The purpose of this research is to create a CNN model for the early identification of skin cancer. The backend of the CNN classification model will be built using Keras and Tensorflow in Python. Different network topologies, such as Convolutional layers, Dropout layers, Pooling layers, and Dense layers, are explored and tried out throughout the model's development and validation phases. Transfer Learning methods will also be included in the model to facilitate early convergence. The dataset gathered from the ISIC challenge archives will be used to both tests and train the model.

Keywords: Skin Cancer; Deep Learning; Image Classification; Neural Network;

1. Introduction

There has been an increase in the incidence of skin cancer over the last decade [1]. Skin cancer is the most prevalent kind of cancer in humans, which makes sense given that the skin is the body's biggest organ [2]. Malignant and nonmelanoma skin cancer are the two main subtypes [3]. Dangerous, uncommon, and ultimately fatal, melanoma is a kind of skin cancer. The American Cancer Society reports that although melanoma skin cancer accounts for just 1% of all occurrences, it has a greater fatality rate than any other kind of skin cancer [4]. Melanocytes are the target of the cancer melanoma. The process begins when an abnormal growth of normally functioning melanocytes gives rise to a malignant tumor. All parts of the body are fair game. Sun-exposed parts like the hands, face, neck, lips, etc., are the most likely to develop this condition. Only if detected and treated early may melanoma tumors be cured; otherwise, they metastasize to other organs and cause a slow, agonizing death [5]. Nodular malignant, superficial spreading cancer, acral lentiginous, and multifocal maligna are all subsets of the melanoma skin cancer family. Nonmelanoma cancers, which include the most common types of cancers including squamous cell carcinoma (BCC), squamous cell (SCC), and increased sebum carcinoma (SGC), account for the vast majority of cancer diagnoses (SGC). Basal cell carcinoma, sebaceous gland carcinoma, and squamous cell carcinoma all develop in the

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uppermost and middle epidermis. This kind of cancer cell seldom metastasizes to other organs. In contrast to melanoma tumours, nonmelanoma cancers are often successfully treated with very little difficulty.

The prevalence of melanoma, a deadly form of skin cancer, is on the rise in many countries. 1 In White populations, the rate has risen by 3-5% per year since the middle of the 20th century and is now between 20 and 60 cases per 100,000 individuals per year. 1 In recent years, the terms "squamous cell carcinoma" and "large cell carcinoma" have come to be used interchangeably to describe the two most frequent types of non-melanoma skin cancer.

The annual incidence in Germany varied from 147.8 to 391.4 per 100,000 people in 2017, adjusted for age. In the United Kingdom, about 152 000 cases reported of keratinocyte adenocarcinoma were detected in 2017.

Keratinocyte carcinomas, like melanoma, have a sharply increasing incidence. However, the prognosis improves with early detection of skin cancer. In the case of melanoma, for instance, the 1-year survival rate is 100 percent when identified at stage 1 of the American Joint Cancer Committee's staging system, but it drops to 53 percent by stage 4[6].

Most individuals in guardian health-care systems, like the UK's, go to their family doctor first when they see anything unusual on their skin.6 This means that doctors in primary care need to be able to tell the difference between common benign skin lesions and more serious ones, like melanoma. If primary care physicians could more accurately diagnose worrisome skin lesions, it would improve patient satisfaction and decrease the need for dermatological expert services, which in turn would save costs. In addition, early detection of skin cancer by more precise evaluations may improve health satisfaction.

Therefore, early detection is the most important component in treating skin cancer. The biopsy is the standard approach used by doctors to diagnose skin cancer. This method is used to take a tissue sample from a suspicious skin lesion so that it may be analyzed for malignant cells. This is a tedious and lengthy procedure that causes a lot of discomforts. The signs of skin cancer may be diagnosed quickly, easily, and affordably with the use of modern computer technologies. Multiple, noninvasive methods are offered for determining if the symptoms of skin cancer are caused by melanoma or another kind of skin cancer. Acquiring the picture, preprocessing it, segmenting the obtained heavily processed picture, identifying the feature of interest, and finally classifying it are the standard steps in skin cancer diagnosis.

Among the most serious health problems in the world is skin cancer, mostly because of its high incidence relative to other forms of cancer. While melanoma has always been a relatively uncommon form of cancer, its incidence has skyrocketed over the last half-century. According to the average number of life years lost due to cancer, it is among the most notable cancers. It's not helpful that melanoma therapy is so pricey. Melanoma accounts for 33% of the total cost of treating skin cancer in the US ($8.1 bn). The two most common types of skin cancer, squamous cells, and basal carcinoma, are highly treatable if caught and treated early. When melanoma is detected at an early stage, the prognosis for the patient's survival over the next five years is almost 100%. Therefore, the most important aspect in minimizing the death rate from skin cancer is early identification.

Growing research suggests that AI and ML may supplement or even change human judgment in the therapeutic setting. Clinical trials have proven that AI/ML algorithms may aid in the detection of skin malignancies, with some even showing that they perform as well as or are superior to consultant dermatologists. AI/ML algorithms may have a significant impact on diagnostic services if similar results can be obtained in primary care environments with a low frequency of skin cancer. While there are a few market-ready tools for spotting signs of skin cancer, no AI/ML algorithms are yet available for use in the diagnostic process in the United Kingdom.

used often in clinical settings for identifying and classifying skin abnormalities. A lack of strong data on the diagnostic performance of AI/ML systems in density, to assist the decision-making of government leaders and commissions on the proper use of AI/ML in medical care, is one of the probable explanations for this lack of utilization.

To say that deep learning has changed the face of machine learning is an understatement. It is the most cutting-edge area of machine learning, and it focuses on developing and optimizing algorithms for artificial neural networks. The design of these algorithms was motivated by studying how the

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brain works. Natural language processing, recognition system, and informatics are only some of the many applications of deep learning. When compared to more traditional machine learning methods, the results produced by deep learning systems in these contexts are outstanding. In recent years, several different deep learning strategies have been implemented for application in computerized skin cancer screening. In this work, we go deep into the topic of using deep learning to identify skin cancer. This paper presents a systematic literature review of traditional deep learning methods, including ANN, CNN , KNN, and GAN, to detect skin cancer.

In recent years, because to advancements in machine learning technology focused mostly on deep learning, hopes for AI have risen, and studies into AI's potential role in healthcare have advanced rapidly[7–10]. Our research made use of the Faster R-CNN (FRCNN) method, which was developed by combining the region proposal network (RPN) and Fast R-CNN (FRCNN) algorithms [11,12]. The R-CNN, which consists of the following 3 sections: region proposal, vector modification, and categorization [13,14], was the first of its kind to perform region-based target identification. Optimizing the R-CNN with a spatial pyramid pooled (SPP)-net led to better detection results [15,16]. The effectiveness of Fast R-training CNNs and testing is due to its use of an inter-loss function, which builds on the strengths of both SPP-net and R-CNN [17]. By combining RPN and Rapid R-CNN into a single network and using "attention" techniques to distribute the convolutional features, FRCNN speeds up and enhances the accuracy of target identification. To be sure, FRCNN has shown superior detection capability in the biomedical field compared to other state-of-the-art algorithms such as SVMs, VGG-16, SSDs, and YOLO [18–20]. The intention of the DFU investigation was identical to our own, and FRCNN has attained the greatest performance for detecting DFUs. This is why we settled on the FRCNN structure for our investigation. In addition to uncontrolled learning models, semisupervised learning methods have seen extensive use in the area of medical research [21,22]. However, we opted for supervised learning in our investigation since diagnosis is a medical activity that needs official training data by health doctors.

Here is how the rest of the paper is structured: Section 2 describes the dataset, the deep learning models, and the performance evaluation metrics and setup, Section 3 describes the performance evaluation results alongside a comparison to the prior research and discussion of the models, and Section 4 wraps everything up.

2. Method and Database

Together, the private sector and academic institutions form the ISIC: Melanoma Project, intending to accelerate the widespread use of digital skin imaging to reduce skin cancer death rates. The International Skin Cancer Identification Consortium (ISIC) has been hosting international competitions for melanoma skin lesion analysis since 2015. Examples of each category may be seen in Figure 1.

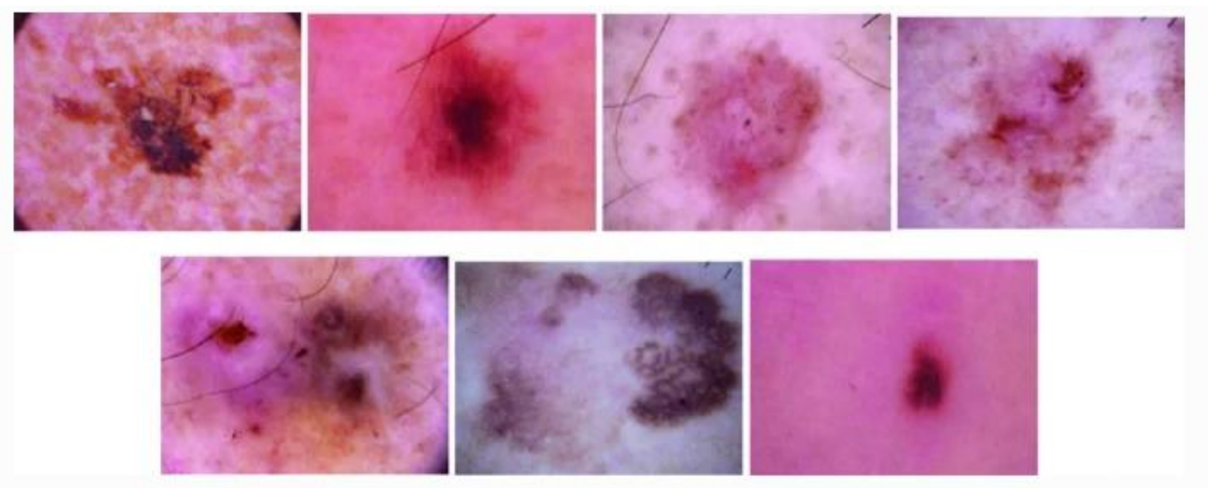

Figure 1: The images of skin cancer.

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Benign ptosis, properly identify, vascular disease, tumor, cytologic nevus, basal cell carcinoma, and keratosis are only some of the skin lesion illnesses included in the initial collection, titled "ISIC 2018," which includes 10,015 photos. The Medical School of Vienna and the University of Queensland gave their permission to acquire these photographs. Each picture has a regular JPEG size of 600*450 pixels.

The second dataset, titled "ISIC 2019," has 25,333 photos of 8 different skin lesion illnesses, including single strand, arterial lesion, carcinoma, cancer, melanomas nevus, malignant melanoma, actinic keratosis, and benign keratosis. All pictures are 1022px wide by 767px high and saved in JPEG format.

Recent successes with deep learning techniques have been linked mostly to an increase in data volume and variety. Machine learning models benefit greatly from being fed massive amounts of data. But gathering such massive amounts of information is time-consuming and expensive. That's why we resort to Data Augmentation. With this method, we may greatly expand the variety and amount of data at our disposal without having to collect any more data at all. Techniques including cropping, cushioning, adding noise, adjusting brightness, and vertical flipping are often used to train massive neural networks using newly generated data from augmented pictures. Table 1 shows information on data augmentation.

Table 1: Data augmentation information

Zoom range	0.1
Rotation range	10
horizontal flip	False
Rescale	1./255
Width shift range	0.1
Height shift range	0.1
Zoom range	0.1

As the name implies, "Image Normalization" is a method for making an image's pixel values more uniform across the board. Before feeding pictures into a neural net, normalizing them may help the network get closer to the global minimum of the error surface during gradient descent. It aids the network in coming together more quickly. Once all the image pixels are scaled, the calculations are much easier for the computer to carry out.

The term "Transfer Learning" refers to a kind of machine learning in which one model's training data is used as the basis for another model's training data on a comparable job. Since training neural network models requires a substantial investment of time and computing power, this method has been widely accepted in the field of deep learning. Knowledge transfer is facilitated by the fact that low-level characteristics, such as forms, corners, edges, and intensities, may be used in several contexts and applied to different tasks in the machine vision domain.

In this work, we use transfer learning to train the CNN using the pre-trained classification weights from ImageNet. Classification task including about 20,000 classes and 14 million training pictures is available at ImageNet ILSVRC. The training speed of the classifier is much improved by using the pre-trained weight for fine-tuning, the limit of a limited amount of training data is eliminated, and convergence is more realistically achieved. The image's edges, points, corners, and other elementary features may be picked up by the CNN's first few layers, and the trained model's increased speed of adaptation can be attributed in part to the use of pretrained weights.

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The seven-class categorization of skin lesion photos is performed using the state-of-the-art CNNs Inception V3, ResNet50, VGG16, MobileNet, and InceptionResnet during training and testing.

3. Performance Model

It is not possible to measure the overall efficiency of a model in a classification task using a single statistic such as Accuracy. Thus, for each kind of skin lesion condition, we assess its Accuracy, Precision, Recall, F1 Score, and Support. To see how effective our model generalizes between classes, we can plot the Confusion Matrix.

Now we'll learn the inner workings of those measures and what they imply.

$TP = True\ Positive,$
$FN = False\ Negative,$
$FP = False\ Positive,$
$TN = True\ Negative;$
$this\ is\ a\ confusion\ matrix,$ shown in Table 2.

Table 2: Confusion matrix

	Positive	Negative	
Positive	TP	FP	TP+FP
Negative	FN	TN	FN+TN
	TP+FN	FP+TN	

If a skin lesion picture is labeled as cancer and the algorithm also classifies it as carcinoma, this is termed a true positive instance. False negatives occur when a picture is annotated as melanoma but is assigned to one of the other six categories. When an image of a skin lesion is flagged by the classifiers as having melanoma when in fact it more closely matches the criteria for one of the other six illnesses, this is known as a false positive case. For a skin lesion picture to be classified as non-melanoma by a classifier, it must first be shown to be a benign lesion. The hyperparameters in Table 3 were utilized to train the CNN models.

Table 3: The hyperparameters of Model.

Optimizer	Adam optimizer
Learning rate	0.0001
Epochs	30
Loss function	Categorical cross-entropy
Batch size	64
Dropout	0.4

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Showing how well the ResNet50 model can classify data. This model needs input photos to be 224 by 224 pixels in size, thus we downsized all the input images to that specification in Table 4. Table 5 shows the accuracy of this model.

Table 4: Confusion matrix of ResNet50

AKIEC	BCC	BKL	DF	MEL	NV	VASC	
AKIEC	115	16	79	7	11	10	0
BCC	33	574	72	4	31	52	2
BKL	11	17	596	1	29	36	0
DF	1	5	6	54	6	5	0
MEL	4	13	106	1	828	170	0
NV	3	15	117	8	135	3690	2
VASC	0	1	0	1	2	3	72

Table 5: ResNet 50 Accuracy

	Precision	Recall	F1 score
Actinic Keratosis	0.69	0.48	0.57
Basal Cell Carcinoma	0.90	0.75	0.81
Benign Keratosis	0.61	0.86	0.72
Dermatofibrom a	0.71	0.70	0.71
Melanoma	0.79	0.74	0.77
Melanocytic Nevus	0.93	0.93	0.93
Vascular Lesion	0.95	0.91	0.93

Indicates how well the MobileNet model can classify data. This model needs input photos to be 224 by 224 pixels in size, thus we downsized all the input images to that specification.

Displays the VGG16 model's accuracy in making classifications. This model needs input photos to be 224 by 224 pixels in size, thus we downsized all the input images to that specification.

Indicates how well the Inception V3 model classifies data.
Due to the specifications of this model, the input photos were scaled down to 299299.

displays how well the InceptionResnet model can classify data. This model needs input photos to be 299 by 299 pixels in size, thus we downsized the input images to meet those specifications. Table 6 shows the accuracy of a different model.

Table 6: CNN actuary.

	Accuracy	Precision	Recall	F1 Score
ResNet 50	85%	85%	85%	85%
MobileNet	85%	85%	85%	85%
VGG 16	87%	87%	87%	87%
Inception	90%	90%	90%	90%

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V3				
Inception ResNet V2	91%	91%	91%	91%

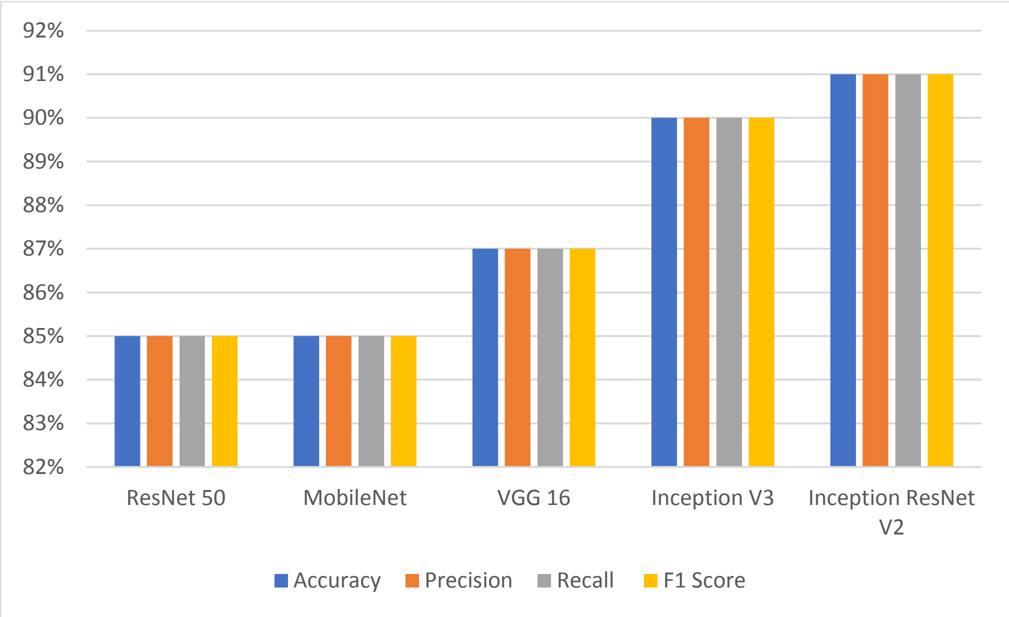

Figure 2: The proposed model accuracy.

6. Conclusion

The two most deadly forms of skin cancer, melanoma, and non-melanoma, account for a significant number of fatalities every year. A recent study found that early diagnosis significantly reduced therapy time, expense, and suffering associated with the more conventional, drawn-out treatment approaches (e.g., chemotherapy). However, an expert understanding of the various malignancies and how they manifest in skin lesions is necessary for proper screening/diagnosis. Some individuals may choose to overlook these lesions because they aren't aware of the symptoms they might indicate or because they can't afford medical attention right away. In recent years, advancements in deep learning and AI have allowed the creation of trustworthy image-based healthcare systems for diagnosis and screening.

To reiterate, the purpose of this study was to create a convolutional neural network model for identifying skin cancer in photos of lesions. Additionally, the data augmentation strategy was investigated as a preprocessing step to improve the CNN model's classification resilience. With an average accuracy of 91%, InceptionResnet V2 emerged as the best model.

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