Deep Learning and Machine Learning to Diagnose Melanoma[1]

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ABSTRACT

The most dangerous disorders include melanoma. Yet, a precise diagnosis of skin cancer is difficult. Recent research has shown that a variety of activities can be performed better using deep learning and machine learning techniques. For skin conditions, these algorithms are highly useful. In this article, we examine various deep learning and machine learning techniques and how they could be applied to the detection of melanoma. This paper provides a number of publicly downloadable datasets, information on common melanoma, instructions for getting dermatology pictures, and more. Once machine learning and deep learning concepts have been introduced, our attention shifts to analysing common machine learning and deep learning architectures as well as popular frameworks for putting machine and deep learning algorithms into practice. Metrics for performance evaluation are then offered. In this section, we will cover the research on machine learning and deep learning and how they can be applied to the detection of melanoma skin illnesses. We also go over potential research avenues and the difficulties in the field. The main objective of this work is to discuss modern machine learning and deep learning techniques for melanoma diagnosis.

Keywords: *SVM; CNN; ResBCU-Net; CAD; Neural Network.*

INTRODUCTION

In recent years, cancer has become a greater threat to human life. It occasionally results in certain human deaths. There are many distinct varieties of cancer in the human body, and skin cancer is one of the deadliest and rapidly spreading types. This disease can be brought on by a number of things, including smoking, consuming alcohol, having allergies, becoming sick, getting viruses, exercising, changing environments, and being exposed to UV rays. Your skin cells' DNA can be destroyed by sunlight. The presence of atypical swellings in a person's body increases their risk of developing cancer. The four most prevalent kinds of skin cancer—actinickeratosis, basal cell carcinoma, squamous cell carcinoma, and melanoma—are what most individuals get. [1]Melanomas, the most unexpected and fatal cancer, are on the rise, according to recent statistics. Early intervention could considerably lower the death rate in the majority of fatal cases. Melanoma primary case detection is difficult and error-prone with the naked eye, necessitating training and experience. Given the scarcity of dermatologists with specialised knowledge, automated and computerised methods are required to reliably identify melanoma. [2]. Doctors employ automated technologies in computer assisted diagnostics systems to make more accurate medical diagnoses. Melanoma segmentation and melanoma identification are two essential CAD capabilities for analysing melanoma lesions. ABCDE traits can be used to identify melanoma malignancy. When

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diagnosing and categorising melanomas, CAD looks for certain criteria in skin lesions. [3]
Some of the attributes are:

Attribute	Explanation
Variance	Melanomas are frequently asymmetrical, or not consistently formed. Noncancerous moles typically have a homogeneous, symmetrical appearance.
Boundary	a noncancerous mole has smooth, well-defined lines, a malignant mole frequently has irregular borderlines or is not well-defined.
Appearance	Melanomas frequently come in a variety of hues or tints. Contrarily, benign moles often only have one colour.
Dimension	A typical malignant growth is more than 6 mm in diameter, or roughly the size of a pencil.
Progression	Melanomas frequently change their appearance, including their size, shape,colour. Unlike the majority of benign moles, melanoma evolves over time.

A melanoma diagnosed at an early stage has a 90% chance of being treated, compared with 50% if the cancer is diagnosed at a late stage [10]. Increasingly high-resolution imaging technologies have been developed non- invasively, it is now easier to diagnose skin cancer or lesions in-situ [4]. Overtreatment (Diagnosed falsely) and under treatment (Diagnosed falsely) are frequently caused by defective diagnostic capability in melanoma. An excessive number of benign lesions are excised for biopsy and pathology analyses due to a false positive diagnosis, which leads to an excessive treatment cost increase. In addition, high-resolution imaging techniques increase diagnostic specificity, and thus reduce unnecessary surgeries and related expenses. Among the most techniques commonly used for imaging used to diagnose skin cancer today are dermatoscopic examinations, optical coherence tomography, reflectance confocal microscopy, and ultrasound.

In order to determine whether an image is cancerous or not, CAD systems use the following method: [15]

1. Input Data
2. Performing pre-processing
3. Identification of segments
4. Extrapolation of features
5. Classification
6. Output Data

To recognize melanoma or non-melanoma from an image, Computer Aided Diagnostics systems use various classification techniques.

In **machine learning**, new algorithms are aimed at making predictions based on data given to it. When testing (new)data is presented, machine learning algorithms are able to detect patterns based on general models created using training data. Images can contain training data in the form of images, pixels, and regions, which may or may not be labeled. Depending on the pattern, it can be low- or high-level. Dermatoscopy, optical coherence tomography, reflectance confocal microscopy, and ultrasound are some of the most commonly used imaging techniques to diagnose skin cancer today. [33][34][35][36]

ALGORITHMS THAT FALL INTO THE DIFFERENT CATEGORIES OF MACHINE LEARNING:

Based on the types of learning problems they address; machine learning algorithms can be categorized into three main groups. The following categories are listed:

Supervised Machine Learning: To facilitate supervised learning, training datasets should conform to a specific format. All instances (data points) are labeled. Each dataset is defined as (a, b) *A * B, where a and b denote a data point and the corresponding true prediction for a. The problem is a classification one if the output b is in a discrete domain. A regression task is one that produces a continuous output.

Unsupervised Machine Learning: As opposed to supervised learning, unsupervised learning does not label datasets. By analyzing similarities between objects, ML can construct a structure from unlabeled data.

Semi-supervised Machine Learning: In this supervised learning task, An insignificant amount of labelled data is used to train the model along with an unlabeled set of data.[16]

Neural Networks: Human brains contain a biological neural network. In addition to being highly complex, it is also capable of performing multiple tasks at once. An intelligent neural network (NN) simulates the behavior of neurons and the human brain. Neurons are replaced by perceptrons as the basic unit of NN. In the figure, we can see that the NN architecture is comprised of 3 layers, the input layer with input feature vectors, the output layer with neural network responses, and the middle layer with neurons (perceptrons) between the input and output layers.[5][6]

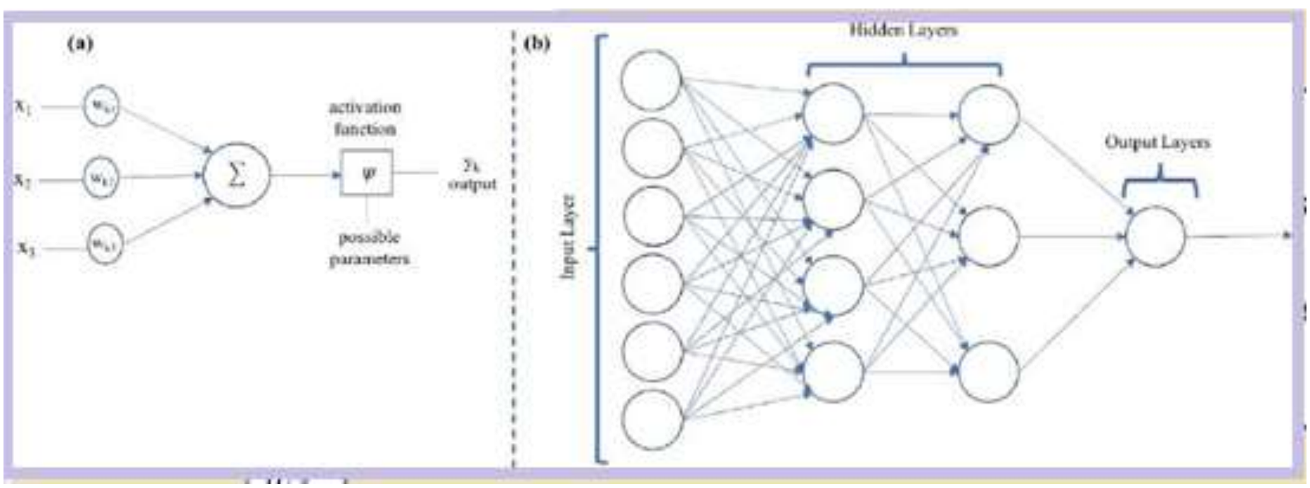

FIGURE 1.3: (a) is the perceptron layer and (b) is the image of Multi-layer NeuralNetwork

Convolution Neural Networks: Most often, artificial neural networks (ANN) are applied to computer vision by using convolutional neural networks (CNN). Computer vision problems are solved with CNNs for two main reasons.CNNs have input and output layers as well as hidden layers. Convolutional layer, pooling layer, and fully connected layer are commonly used for creating hidden layers.[14]

Convolutional Layers: The output of these layers is passed along to the next layer to simulate the response of a neuron to visual stimulation.

Pooling Layers: A neuron in the next layer is derived from the outputs of neurons in the first layer. This layer has the purpose of reducing the parameters and computations in the network.

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Fully-connected Layers: Every neuron in each layer is connected to every neuron in every other layer.[8][10]

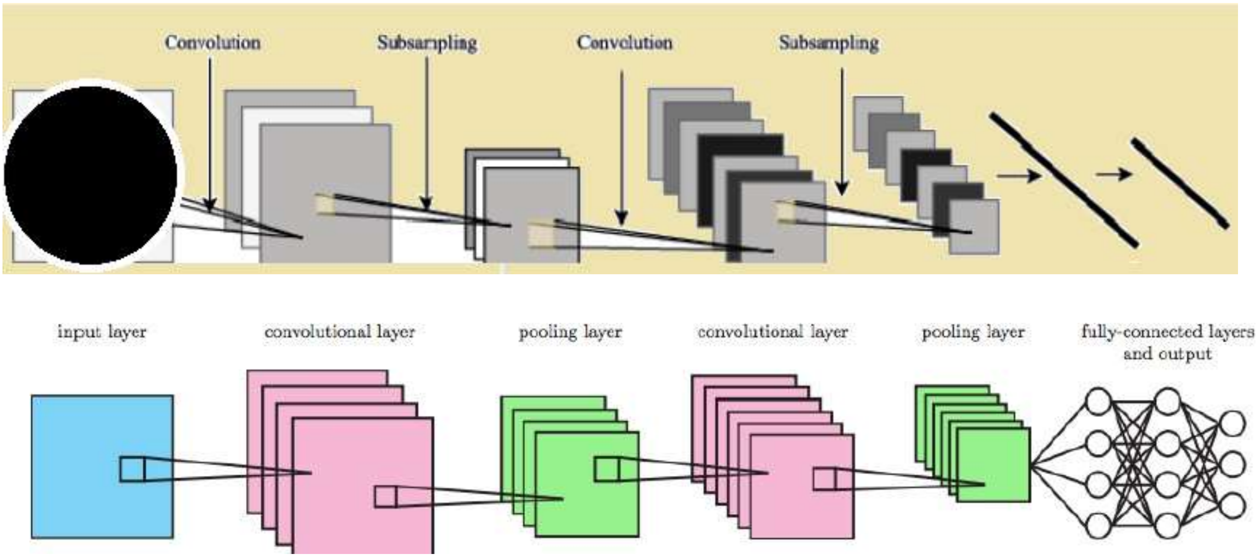

FIGURE 1.4: A convolutional neural network

Neural networks serve as the fundamental building blocks of deep learning, a type of machine learning. The two forms of deep learning approaches are supervised and unsupervised.

in a similar way. Feed Forward Completely Connected Deep Neural Network (FNN): At a low computational cost, FNN can handle classification problems in a general-purpose, flexible manner. They are essentially a DNN version in which the neurons in the current layer are linked to those in the preceding layer.[9]

Convolutional Forward Feed Deep Neural Networks (CNN): Because it takes input from neurons in the layer below, a CNN is highly adept at processing spatial data. CNNs require less processing than FNNs do

. There is no output layer in deep belief networks (DBNs), which are made up of restricted Boltzmann machines (RBMs), another class of neural network. DBN is excellent for pre-training activities since it can recognise features. For training, unlabeled datasets are also required.

A class of neural networks known as stacked auto encoders (SAE) have an equal number of inputs and outputs. There are numerous auto encoders in SAE. Performance-wise, SAE is comparable to DBN, however it performs better with smaller data sets.

SKIN LESION DATA SETS DESCRIPTION

Good data has always been a requirement for an algorithm to work. High quality data and trustworthy skin disease diagnosis labels are essential for creating advanced algorithms. The main image types that are utilised to identify skin illnesses include clinical images, dermoscopies, and pathological images. Images of skin lesions are typically taken with mobile cameras and saved as medical records for future reference. An openly accessible dataset of dermoscopy images is the PH2 dataset1 by Mendonca et al.

In 2003, 40 melanomas, 80 atypical nevi, and 80 common nevi were all noted. The dataset's images include some medical annotation, such as clinical and histological evaluations, medical segmentation of lesions, and several dermoscopic criteria (dots and globules, streaks, regression areas, and blue-whitish veil). Because a dataset with rich meta data has significant meta data, it is frequently used to assess algorithms for melanoma diagnosis. The dataset is used to assess melanoma diagnostic algorithms. The International Skin Imaging Collaboration (ISIC) gathered a sizable dataset of dermoscopy images from eminent dermatologists that contained over 20 000 images.. The three types of images displayed here are melanomas, seborrheic keratoses, and nevi. The first two are benign skin tumors, whereas Melanoma is a malignant skin tumor. Also included in the validation set are 150 additional images for evaluation. Tschandl released a dataset containing dermoscopy images collected and stored through various acquisition methods in a 10000-hour training program for Human Against Machine (HAM10000). [17]The ISIC archive makes public the 10015 dermoscopy images that comprise the dataset. It includes all relevant diagnostic categories in dermoscopy. An examination of the biopsies confirmed all the diagnoses of melanomas, while other diagnostic methods and expert consensus confirmed the diagnoses of nevi (24%), including analysis of images with no temporal changes (22%). Dermanet provides articles, photos, and videos about dermatology online as an independent online medical education resource. Dermanet offers a variety of skin care information by combining innovative media with dermatology information. Dermanet provides more than 23000 photographs of skin diseases. If you click the image, you can enlarge it. You can also browse image categories to find images. Licensed high-resolution images can be purchased and licensed by users for publication purposes. The Department of Dermatology at the University Medical Center Groningen (UMCG) has provided 70 melanoma and 100 nevi images for MED-NODE dataset2. By using the MED-NODE system, MED-NODE detects skin cancer using macroscopy images. Online dermatology resources can be found at DermIS.net. The main body of the book contains elaborate image atlases (DOIA and PeDOIA) that include diagnoses and differential diagnoses, case reports, and additional information on most skin diseases. Additionally, it has detailed image atlases (DOIA and PeDOIA), which contain diagnostic information, differential diagnoses, and case reports to help with the diagnosis of most skin diseases. 102451 MoleMap7 images are included in this dataset, which features 25 skin types and 22 benign categories. One of the most common types of cancerous tumor is melanoma (pink melanoma, ordinary melanoma, and lentigo melanoma). The next most common form is basal cell carcinoma.

Dataset	Data Size	Image type	Disease type
ISIC dataset	3297 images	Dermoscopic and clinical images	Melanoma,seborrheickeratosis, benign nevi
PH2	200	Dermoscopic images	Melanomas
HAM100000	10,015	Dermoscopic images	Pigmented lesions
Dermnet	25,000	Dermoscopic, clinical and pathology images	23 categories
IAD	2800	Dermoscopic and clinical images	Melanoma and benign lesion
MED-NODE	170	Clinical images	Melanoma and nevi
DermIS	>1000	Clinical images	All kind of skin diseases
MoleMap	102,451	Dermoscopy and clinical images	22 benign categories and 3 cancerous categories

FIGURE 2: Public datasets for skin disease

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FEATURE EXTRACTION

Extraction of pertinent features is essential for a successful categorization procedure. ABCD, GLCM, and local binary features of the skin lesion can all be simultaneously extracted. ABCD includes: The asymmetry index (A), border irregularity (B), colour score (C), and dimension (D) of the lesion are all assessed using the ABCD-rule. While benign skin lesions are more prevalent in symmetrical lesions, asymmetrical lesions have a higher likelihood of malignant skin lesions.

The GLCM (Gray Level Co-Occurrence Matrix) includes: The frequency of grey values that are consistent across pixels is taken into account by the GLCM technique. To assess the texture of the image, the relationship between the reference pixel and the pixels around it must be established. Among the characteristics retrieved from symmetrical directional GLCMs for texture characterisation are energy, contrast, correlation, and homogeneity. Local binary pattern (LBP) features: Surface texture characteristics are defined by the Local Binary Pattern. The LBP histogram distribution structure could be used to determine texture regularity. In applications like categorization and identification, LBP features are used to encode texture-based data. Local Binary Patterns derive their origin from evaluating structures in two dimensions.[14]

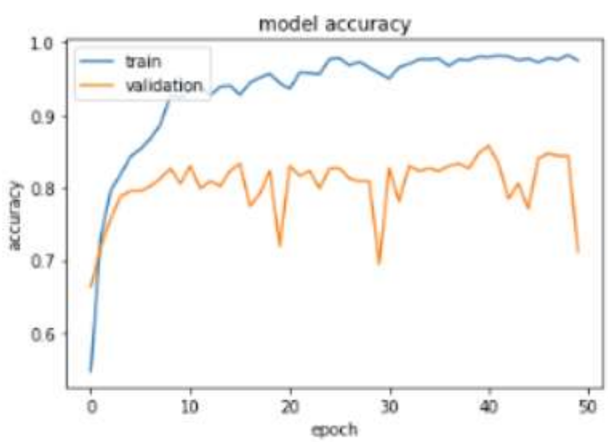
```
#Visualize one instance of all the class present in the dataset.

#image_dataset_from_directory() will return a tf.data.Dataset that yields batches of images from the subdirectories.
#label_mode is categorial, the labels are a float32 tensor of shape (batch_size, num_classes), representing a one-hot encoding of the class index.
image_dataset = tf.keras.preprocessing.image_dataset_from_directory(data_dir_train,batch_size=32,image_size=(180,180),
                                                                    label_mode='categorical',seed=123)

#all the classes of Skin Cancer
class_names = image_dataset.class_names

#Dictionary to store the path of image as per the class
files_path_dict = {}

for c in class_names:
    files_path_dict[c] = list(map(lambda x:str(data_dir_train)+'/'+c+'/'+x,os.listdir(str(data_dir_train)+'/'+c)))

#Visualize image
plt.figure(figsize=(15,15))
index = 0
for c in class_names:
    path_list = files_path_dict[c][:1]
    index += 1
    plt.subplot(3,3,index)
    plt.imshow(load_img(path_list[0],target_size=(180,180)))
    plt.title(c)
    plt.axis("off")
```

Related work	Types of features extracted	Work Accuracy
Mabrouk et al.[44]	GLCM	91%
Takruri et al.	Wavelet features	87.1%
Codella et al.[53]	Sequential Pattern Mining	93.1%
Pillay et al.[48]	ABCD	75.295%
Puspitasari et al.[49]	GLCM	83.86%
Nabil et al.[50]	ABCD	90%
Proposed Method[55]	ABCD+GLCM+LBP	97.7%

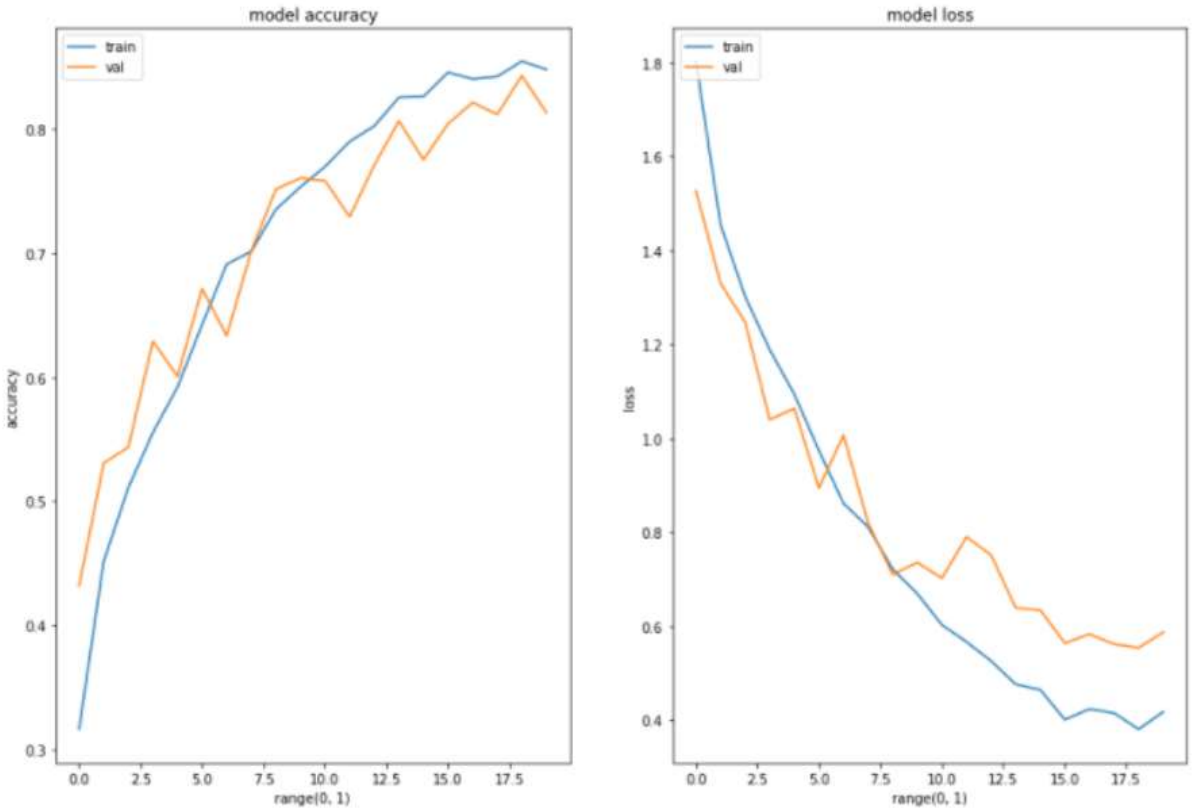
FIGURE 3: Study on types of features extraction

MACHINE LEARNING AND DEEP LEARNING FRAMWORKS

In light of the popularity of machine and deep learning, Frameworks for learning that are open source have been created to build deep learning models with complex architectures and large scales easy to implement.



validation accuracy:85.76%



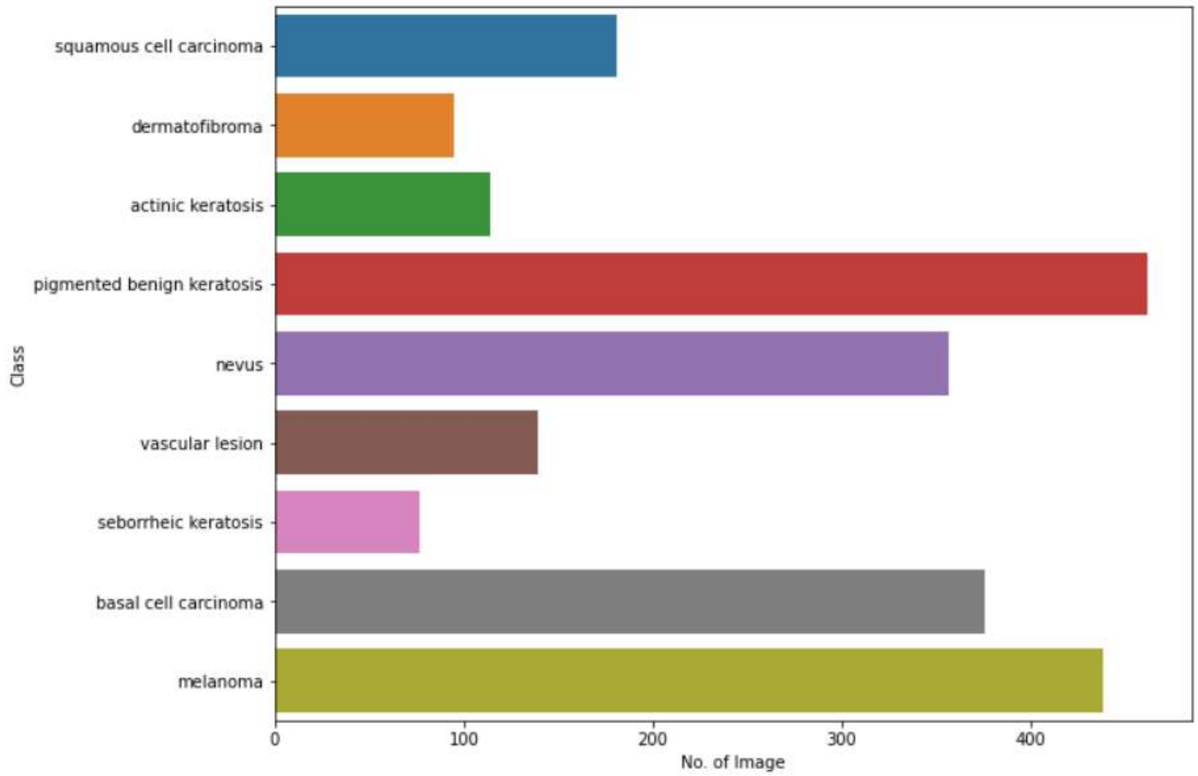
DATA PREPROCESSING

When data is pre-processed with machine and deep learning, the diagnosis of skin diseases becomes much easier and more accurate. In general, deep learning networks typically receive images(data) with determinate pixel sizes. That is because there are huge differences between the image resolutions of datasets (e.g., ISIC, PH2 and AtlasDerm). Images could be distorted or lose significant information if resized or cropped directly into required sizes. Keeping the aspect ratio of the image while resizing the shortest side is one solution to this problem. The mean value is subtracted from the images before a deep learning network is fed with images, and the standard deviation is calculated over a given training set. A standard deviation is calculated based on the entire training set bysubtracting the images from the mean value of the deep learning network.

DATA AUGMENTATION

The training of a deep network, in order to avoid overfitting, a lot of data is needed and achieve excellent results. A large amount of labeled training data is usually not available for many applications, such as diagnose a skin condition. There are a great deal of limitations in medical image analysis due to several factors, such as the rarity of diseases, patient confidentiality, the need for expert labeling, and the high cost of collecting medical data.

Augmentation of data (DA) is one way to resolve labeling problems, but the augmented images usually have a similar distribution to the original, which leads to limited performance improvements. We created skin lesion images by generating adversarial networks (GANs) to fill in the data vacuum in the real image distribution.[23].



SKIN LESION SEGMENTATION

A technique is suggested for segmenting lesions into three categories using the ISIC 2107 dataset. Our method performs better for difficult skin lesions when compared to the sole method that is currently available for the multi-class segmentation of dermoscopic pictures. Also, the technique we created for binary segmentation and lesion identification has been examined, and the outcomes have been contrasted with those of other cutting-edge techniques. The proposed strategy is effective at delivering findings that are even more dependable for clinical applications with little training data, according to the results of the studies. Using neural networks to segment images performs better than other currently used methods. In this paper, a neural network based on CNNs is proposed for segmenting medical images. This network, known as ResBCU-Net, is an enhancement to the U-Net system and makes use of Residual blocks, Batch normalisation, and Bi-directional ConvLSTM. We also provide ResBCU-Net(d = 3), which makes use of densely linked layers at a bottleneck location in addition to ResBCU-Net. The proposed neural network is trained and tested using the ISIC 2018 dataset, which includes of 2594 photos of melanoma malignant skin. The network segmentation performs more precisely than other cutting-edge substitutes. a novel system for classifying skin lesions. In specifically, feature representations are learned from dermoscopy pictures using the Adaptive Feature Learning Network (AFLN). By utilising an ensemble learning approach, the AFLN model is able to include data from many scales. We solve the overfitting issue brought on by imbalanced training by employing a Difficulty-Guided Curriculum Learning (DGCL) method and stepwise training. The Select-The-Biggest-Connected-Region (STBCR) method is developed to address the over-segmentation issue in the fusion model..[14]

```
def class_distribution_count(directory):

    #count number of image in each classes
    count= []
    for path in pathlib.Path(directory).iterdir():
        if path.is_dir():
            count.append(len([name for name in os.listdir(path)
                               if os.path.isfile(os.path.join(path, name))]))

    #name of the classes
    sub_directory = [name for name in os.listdir(directory)
                    if os.path.isdir(os.path.join(directory, name))]

    #return dataframe with image count and class.
    return pd.DataFrame(list(zip(sub_directory,count)),columns =['Class', 'No. of Image'])

df = class_distribution_count(data_dir_train)
df
```

	Class	No. of Image
0	squamous cell carcinoma	181
1	dermatofibroma	95
2	actinic keratosis	114
3	pigmented benign keratosis	462
4	nevus	357
5	vascular lesion	139
6	seborrheic keratosis	77
7	basal cell carcinoma	376
8	melanoma	438

Datasets	Method	Description
ISIC 2016 and PH2[62]	FCN	Design a novel loss function based on the Jaccard distance.
ISIC 2016 and PH2[61]	Multistage FCN	Introduce a new parallel integration method to combine information from multiple segmentation stages
ISIC 2016 and PH2[59]	GAN	Consist of a segmentation network based on U-net and a discrimination network linked by certain convolutional layers.
ISIC 2017[63]	FrCN	A full resolution convolutional network.
ISIC 2017[64]	CDNN	A convolutional-deconvolutional neural network with smaller convolutional kernels and include color information for network training.
ISBI 2017[65]	MobileGAN	Combine 1-D non-bottleneck factorization networks with position and channel attention modules
ISIC 2017[60]	YOLO and Grabcut	Detect skin lesion location with the YOLO model and segment images with GrabCut.
ISIC 2017[66]	cGAN	Introduce a factorized channel attention as the encoder of cGAN to exploit both channel attention mechanism and residual 1-D kernel factorized convolution.
ISIC 2017[57]	ResBCU-Net	ResBCU-Net, is an extension to the U-Net system. In addition to ResBCU-Net, we present ResBCU-Net(d = 3) that takes advantage of densely connected layers at a bottleneck region.
ISIC 2018[41]	AFLN	Using a Difficulty-Guided Curriculum Learning (DGCL) method with stepwise training

Table 1: Different Segmentation Methods for skin lesion segmentation

SKIN LESION CLASSIFICATION

CAD systems for the diagnosis of dermatological diseases typically include a classification step at the end of the workflow. A skin disorder classification algorithm may provide binary (e.g., benign or malignant) or ternary results depending on the purpose of the classification algorithm. The classification of skin diseases has been accomplished using several methods of deep learning.

Datasets	Data Size	Model Description	Accuracy
ISIC 2019[67]	25,331 images	Multi-class classification using statistical prism-based fractal signature	87%
ISIC 2017[68]	129,450 images	Self-supervised Topology Clustering Network (STCN)	87.3%
ISIC 2019 and PH2[69]	Not Defined	DenseNet201 combined with Fine KNN or Cubic SVM	(92.34% and 91.71%) for the ISIC 2019 dataset, 99% on the PH2 dataset.
Khanh Hoa General Hospital[70]	33 images	A hybrid framework consisting of the Stokes- decomposition method and various artificial intelligence (AI) models.	100%
ISIC-17, ISIC-18, and ISIC-19[71]	25,331 images	Deep Convolution Neural Network (DCNN)	94%
(ISIC) 2016, 2017, and 2018[30]	25,331 images	full resolution convolution network (FrCN).	Not Defined
ISIC 2016 and PH2[72]	3672	A Multi-Class Multi-Level (MCML) classification algorithm	96.47%
ISIC 2018 and HAM10000[73]	25,331 images	GoogLeNet Inception-v3	Not Defined
DermNet, IEEE DataPort, DermatoWeb[74]	Not defined	Eff2Net	84.70%

Table 2: Skin lesion classification methods (part1)

Datasets	Data Size	Model Description	Accuracy
ISIC 2017[75]	Not defined	dynamic graph cut algorithm for skin lesion segmentation followed by a probabilistic classifier called as Naïve Bayes classifier	94.3% for benign cases, 91.2% for melanoma and 92.9% for keratosis
ISIC 2019[76]	Not defined	FusionM4Net	78.5%
ISIC 2019[77]	Not defined	Hierarchy-Aware Contrastive Learning with Late Fusion (HAC-LF)	87.1%
HAM10000[78]	Not defined	EfficientNets B0-B7	87.91
ISIC 2019[79]	Not defined	CS-AF: A cost-sensitive multi-classifier active fusion framework	Comparative study
spectral data of skin tumors[80]	617 images	convolutional neural networks classification of skin tumors based on Raman spectra analysis	ROC AUCs of 0.96 (0.94 – 0.97; 95% CI), 0.90 (0.85–0.94; 95% CI), and 0.92 (0.87 – 0.97; 95% CI) for classifying a) malignant vs. benign tumors, b) melanomas vs pigmented tumors and c) melanomas vs seborrheic keratosis respectively.

Table 3: Skin lesion classification methods (part2)

CONCLUSION

The use of deep learning to identify skin illnesses has attracted a lot of interest in recent years. There are still many difficulties in this area. Unlabeled, noisy, and unbalanced datasets are a few of them. Several deep learning and machine learning algorithms still lack the ability to explain[13]. The paper offers a thorough examination of developments in deep learning and machine learning-based skin disease diagnoses. We started off by talking about the various skin conditions. The fundamentals of machine learning and deep learning were discussed in our second conversation. The discussion of all the datasets and data kinds related to skin diseases was the third phase. After categorising and segmenting datasets, we examined every machine learning and deep learning technique we used.

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