A Review on Detection and Diagnosis of Melanoma Carcinoma Using Deep Learning

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Abstract. Skin disease is perhaps the most widely recognized malignant growth, and it creates because of an assortment of dermatological conditions. It is divided into numerous categories depending on morphological characteristics, color, structure, and texture. For patients with skin cancer to have a low death rate, early and prompt detection and diagnosis of malignant skin cancer cells is crucial. Dermoscopic pictures currently have image quality restrictions, such as color, artefact, and blur, which can make diagnosis difficult. Early and accurate diagnosis of skin disorders is challenging due to cost, effort, overfitting, larger feature dimension, and low detection accuracy. To address these concerns, we intend to present the most effective Network Model for classifying skin diseases. The skin lesion zones are then efficiently segmented using a new segmentation procedure. This review/survey paper will discuss the recent research on skin lesion classification using Deep Learning.

Keywords: Skin lesion classification · Segmentation · Convolutional network model · Deep learning · Convolutional neural network

1 Introduction

When some cells in the body grow too quickly, they can spread to other places in the body. This is called "cancer." Each human body is made up of up to a million cells. A cancerous condition can develop anywhere any of these cells are located. Human cells create and isolate (called cell division) to make new cells as the body needs them. Malignant growth happens when this typical framework is screwed up by hereditary issues. Cells begin to develop at a wild rate. Some of these cells can work together to make a tumour, which is a type of growth. It could be cancerous or not cancerous. One that is malignant is one that can grow and spread all over the body. In medicine, a benign tumour is one that has the chance to grow but not spread. A condition called skin cancer is when abnormal cells in the epidermis, the outer layer of the skin, grow too quickly. This is caused by damage to DNA that hasn't been repaired. These changes make skin cells grow quickly, which leads to tumour. The four major kinds of skin cancer are BCC, SCC, melanoma, and Merkel cell carcinoma (MCC); however, there also exist many kinds of skin cancers.

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2 Skin Cancer

As per the W.H.O, there were 1,329,779 new instances of skin malignant growth in 2018. Melanoma kills many individuals who pass on from skin disease. This year, about 287,700 people are predicted to get melanoma. Nearly 6700 deaths are expected. The number of skin cancer deaths doesn't matter. Even with high-level treatment, advanced stage malignant melanoma has a 15% survival probability if found early.

2.1 Deep Learning (DL) Techniques

DL has exhibited promising result in segmenting skin infections, a tough topic in computer vision. Various grounded models of deep literacy have been presented. These techniques give excellent skin lesion segmentation results. These architectures include DCNNs, U-Nets, Fully Convolutional Neural Networks (FCNs), Deep Fully Convolutional Neural Networks (FCNNs), and Convolutional DE-Convolutional Neural Networks (CDCNN). Table 1 shows the differences between networks and their use in deep learning.

Table 1. Differentation of network and between networks and its application used in deep learning Techniques

Types of networks	Details of network	Advantage	Disadvantage	Ref paper
DNN	This model utilizes multiple layers to allow for non-linear relationships. It can be used to analyse regression data or to classify data	It is widely used and accurate	There is a problem with the Learning Process, as errors are propagated back to previous layers, where they become minor	[11]
CNN	A network like this is good for processing 2D data since it uses convolutional filters to create 3D images	Execution is great and Learning process is quick	The process of categorizing requires a great deal of labelled data	[1, 5, 6, 9, 13, 15, 21, 24, 25]
Recurrent Neural Network (RNN)	It can learn sequences and distribute weights between steps and neurons	The NLP experts are profoundly precise in analyzing discourse, recognizing characters, and performing other NLP tasks	Gradient vanishing and massive data collecting present many obstacles	[20]

(*continued*)

Table 1. (*continued*)

Types of networks	Details of network	Advantage	Disadvantage	Ref paper
DCNN	DCNN is the number of layers in a network. Modern topologies utilised in cutting-edge applications have 50–100 layers	Deep CNN with more than 5 hidden layers accurately predicts and extracts more informative features	It needs a lot of data to outperform other tactics. Training is costly due to the complexity of data models	[3, 8, 10, 14, 17–19, 22]
Fully Convolutional Neural Network (FCNN)	Fully convolutional means the network has no fully linked layers or MLPs, which are often found near the network's end	It finds the traits without human interaction. It learns distinctive qualities for each class from a vast number of images of cats and dogs	Inability to encode the item's position and orientation relative to the input data	[23]
SNN	In parallel with two different input vectors, it is an artificial neural network that produces equivalent output vectors	Class disparity is more resistant	it is slower than normal classification type of learning	[2]

3 Dataset

A dataset (likewise spelled 'informational index') is an assortment of crude measurements and data created by an exploration study. The motivation behind Datasets is to extract from straightforwardly speaking with the data set utilizing basic SQL explanations. The Dataset's objective is to serve as a small local replica of the data that you bothered about so that you don't have to make costly high-inertia database decisions in the future. A Dataset is the most fundamental information container in PyMVPA. It is the most basic sort of data storage, as well as a standard compartment storing the outputs of most algorithms. As an illustration. An informational index is a collection of numbers or characteristics that pertain to a specific topic. A dataset is made up of the grades of all students in a certain class, for example. The number of fish ingested by each dolphin in an aquarium is referred to as a dataset. By pointing to the article, the publicly available informational index used for skin characterization, division, and discovery is shown in Table 2. The majority of the analysts used a range of datasets to develop their own models and calculations.

Table 2. Dataset for melanoma classification and segmentation

S. No	Dataset	Total no. of images	Images for melanoma skin lession	Images for non-melanoma skin lession
1	DERMOFIT	1300	331	969
2	HAM10000	10015	1113	8902
3	ISBI-2017	600	240	360
4	ISBI-2016	900	379	521
5	ISIC-2016	12000	2750	9250
6	ISIC-2017	13786	1019	12767
7	ISIC-2018	10015	3781	6234
8	ISIC-2019	25331	12875	12456
9	PH2	200	40	160

4 Distribution of Classes

The below Fig. 1 easily states that the distribution of classes according to the dataset and experimenter frequently and infrequently used the dataset. Most of the experimenter used the combination of one or further dataset to classify and member the skin lesion and used the dataset with some other armature or transfer literacy frame to achieve their delicacy.

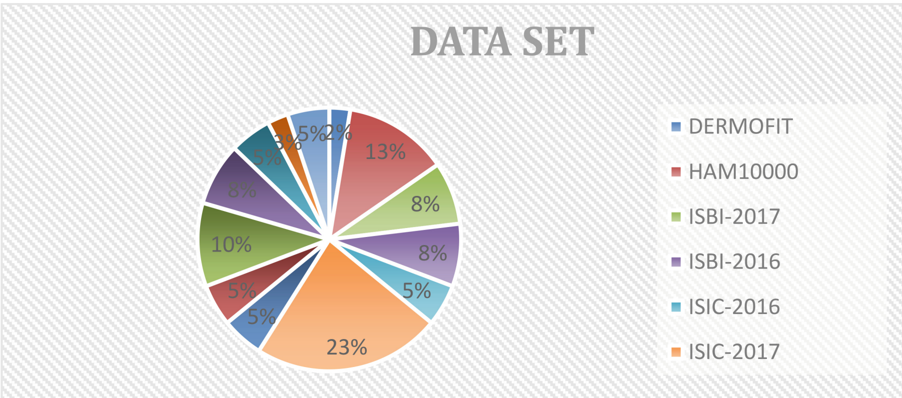

Fig. 1. Distribution of classes according to the dataset

5 Literature Survey

Predicted and investigated earlier work from 2021-2020 in the Table 3. The table below summarises our findings. The table comprises four columns: the reference title, first author, and publication year, the purpose, the method or model employed, and the dataset, and the significant results uncovered when analysing the papers submitted. Several methodologies and algorithms were used to obtain its accuracy. At the end of each investigation, we realised that the network model requires very few datasets. This was done via pixelwise correlation in [2] to sharpen the irregularity and segment the skin lesion. Rather than changing organization boundaries, they utilize Dual Encoder Architecture to work collaboratively. Their dilatation rate differs from ADAM's. The solution outperforms U-Net in both the ISBI2017 and ISIC2018 datasets, highlighting the usefulness of both the dual encoder architecture as well as the adaptive dual attention module in enhancing the segmentation process of skin lesion. [3] In order to screen melanoma, the lesions changes are monitored in short time frame. The global features are extracted from dermoscopy by proposing tensorial neural network. They used a spatial transformer network to improve detection performance and invented the SegLoss regularisation factor. [1] Segmenting and categorising skin lesions. In this, the MB-DCNN method performs both the operations such as segmentation as well as classification. This method involves coarse segmentation network, an updated segmentation network (enhanced-SN) and a mask-guided classification network. This processing creates class imbalance as well as hard easy pixel imbalance. [4] In this study, uneven learning focuses on smaller or more complicated minority courses. The proposed SPBL (Self-Paced Balance Learning) method tries to generate a balanced representation of all classes. [5] According to the authors, a multistage unit-vise deep dense residual network along with transition and supervision blocks can support dense and minimal skip residual learning. Each layer may analyse the previous layers' features locally and less difficultly than its counter network.

6 Skin Lesion Detection in Melanoma Skin Cancer

The ABCD technique can detect melanoma skin cancer, which is lethal. The ABCD rule helps physicians, nurses, and patients identify melanoma-like skin lesions. Melanoma can appear suddenly on the skin. In or near a mole or other dark area on the skin. That's why knowing your moles' colour, size, and placement on your body is critical to spotting changes (Fig. 2).

Table 3. Literature survey

Ref no	Objective of the paper	Algorithm/model	Dataset	Result findings
1	Skin lesion segmentation	Skin lesion segmentation, ADAM, global context modelling, Dual encoder architecture, deep learning	ISBI2017 dataset and ISIC2018 dataset	U-Net is less effective than dual encode architecture in enhancing the segmentation of skin lesions in both the ISBI2017 and ISIC2018 tests
2	To find the variation in the lesion for a short period of time during melanoma screening	Siamese Neural Network, Tensorial Regression Process, convolutional neural networks	SD-198 SD-260	A clinical melanoma centre's in-house dataset of 1,000 lesion images was created to test the suggested technique
3	Skin lesion segmentation and classification	MB-DCNN, mask-CN, coarse-SN, and enhanced-SN	ISIC-2017 PH2	The MB-DCNN model evaluated on ISIC-2017 and PH2 datasets, yielding 80.4% and 89.4% Jaccard file for skin sore division and 93.8% and 97.7% AUC for skin sore grouping
4	Skin disease recognition, class imbalance, and complexity level	SPBL	SD-198 SD-260	With only six training cases, the SPBL can gradually detect variations in symptom border, colour, and lesion site variations. The researchers evaluate two unbalanced data sets that contain clinical skin disease detection tasks and other imbalanced tasks

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Table 3. (*continued*)

Ref no	Objective of the paper	Algorithm/model	Dataset	Result findings
5	Skin lesion classification	Patch-based attention method, deep learning, Diagnosis-Guided Loss Weighting	HAM10000	The utilization of a fix-based consideration system works on mean awareness by 7%. Class adjusting further develops mean responsiveness fundamentally, while finding directed misfortune weighing works on mean awareness by 3%
6	Skin Cancer Classification using Unit-vise neural network	Deep Learning, Unit-vise, Residual Learning	ISIC-2017 and ISIC-2018	Achieved accuracy of about 98.05%, thus ISIC-2018 challenge outperformed existing ISICs
7	Skin lesion diagnosis	Multimodal convolutional neural network, deep Learning, interpretability	HAM10000	Multimodal model enhances sensitivity and AUC SEN 80 by 72 and 21% respectively. Time's complexity must be decreased. IM-CNN also enhances sensitivity, AUC, and AUC SEN 80 by 72%, 9%, and 21% over a single model
8	Skin lesion classification	ARL-CNN	ISIC-2017	The ARL-CNN model performs better, with an AUC of 0.875 for melanoma and 0.958 for seborrheic keratosis

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Table 3. (*continued*)

Ref no	Objective of the paper	Algorithm/model	Dataset	Result findings
9	Skin lesion segmentation bi-directional dermoscopic feature learning, multi-scale consistent decision fusion	Multi-scale consistent decision fusion (mCDF), Bi-directional dermoscopic feature learning (biDFL)	ISBI-2016 ISBI-2017	Mostly, the lesions are uneven with poor contrast. The main reason for inadequate skin segmentation
10	Classify the melanoma lesion utilizing Deep Convolutional Neural Network	DCNN, Fisher vector, Residual network	ISBI 2016	To eliminate the complexity of the training process and to make it more feasible with minimal training samples, the framework leverages a pre-trained CNN as a feature extractor
11	Mobile diagnosis Skin Disease Classification using Deep Neural Network for Herpes Zoster Disease	Biomedical image processing, Deep Neural Network convolutional neural networks, deep learning	SD-198 SD-256	The suggested KDE-CT greatly enhances corruption robustness than other existing techniques. With MobileNetV3-Small training, performance improved
12	Challenge of this paper is to establish high-class and interpretable CAD model using Histopathological Image	Deep Learning, CAD model, Attention mechanism	Private dataset	Based on the experimental results, the DRA Net outperforms baseline models with equivalent parameter sizes while using less model parameters. DRA Net is designed to identify 11 different skin illnesses using real histology images collected over ten years

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Table 3. (*continued*)

Ref no	Objective of the paper	Algorithm/model	Dataset	Result findings
13	To detect and diagnose diverse kinds of skin disorders at various stages	Convolutional neural networks, Style GAN, Dense Net	ISIC2019	Our classification approach outperforms the ISIC2019 dataset by 93.64 percent. Improve the automatic classification system
14	A method to improve convolution neural networks using regularly spaced shifting for the classification of skin lesions	Image processing, deep learning, skin lesion classification	HAM10000	The ensemble + shifting model outperforms deep networks with shifting by 3% and the basic network by 6% in all classification tests. A vast set of displacements was defined by the Shifted MobileNetV2 + Google Net, which covered various changes of the original input image
15	Adopting transfer learning to efficiently classify the skin lesions via labelled data	Deep learning, multi-view filtered transfer learning network	ISIC 2017	Using the ISIC 2017 dataset, the skin lesion classification result showed an average AUC of 91.8%
16	To overcome the issues of automatic lesion detection and segmentation	Deep learning-based encoding and decoding network pixel-wise classification melanoma and skin lesion segmentation	ISBI 2017 PH2	On the ISIC 2017 dataset, skin lesion classification experiments complete classification jobs with an average AUC of 91.8 percent on Melanoma and Seborrheic Keratosis

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Ref no	Objective of the paper	Algorithm/model	Dataset	Result findings
17	To classify skin disorders	Deep Convolutional Neural Network	Private dataset of Human face skin disease sample from Wuhan Hospital [China]	Operating time of RESNET 152 with triple loss on 4GB CUPA cores. The GPU is 34142 s when tuning Inception. The investigation employed four forms of skin diseases as data. Despite 12000 input photos and 2000 test images, only 10% of training data is validated
18	Skin disease classification	Deep neural networks, Balanced mini-batch logic, Hybrid method, Loss function	HAM10000 ISIC 2019	The technique not only outperforms the original approaches by 4.65% (86.13 vs. 81.48), but also reduces recall standard deviations by 4.24. (From 11.84 percent to 7.60 percent)
19	To study the effect of image noise on the classification of skin lesions	Deep convolutional neural network	Dermofit Image Library dataset	A little reduction in accuracy is shown when images are tainted with Gaussian noise. The noise in the images decreases the accuracy of skin lesion categorization

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Table 3. (*continued*)

Ref no	Objective of the paper	Algorithm/model	Dataset	Result findings
20	The lesion boundary segmentation is vital to locate the lesion accurately in dermoscopic images and lesion diagnosis of different skin lesion types	skin lesion segmentation, ensemble segmentation methods, deep learning, melanoma, instance segmentation, semantic segmentation	ISIC2017 PH2	The result showed that in the proposed ensemble method Ensemble-S achieved higher performance for clinically benign cases, melanoma patients, and seborrheic keratosis cases
21	To segment the skin cancer	Deep supervised learning, conditional random field (CRF), multi-scale feature	ISIC 2017 PH2	Post-processing of contour refinement can be used to improve the results of a conditional random field (CRF) model
22	To classify, detect and segment dermoscopy images for analyzing skin lesion	Convolution neural networks, learning, end-to-end multi task framework, melanoma	ISBI 2016 ISIC 2017	Assist in 40 epochs with learning rate 0.0001 and Loss function based on focal loss and Jaccard distance to alleviate severe class imbalance concerns in actual dermoscopy pictures
23	This paper presents a framework for preventing skin cancer by both segmenting and classifying lesions	CAD, FCN, CRF, Dense Net, encoder-decoder	HAM10000	The suggested model performed well on the publicly available HAM10000 dataset, with 98 percent accuracy, 98.5 percent recall, and 99 percent AUC score respectively

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Table 3. (*continued*)

Ref no	Objective of the paper	Algorithm/model	Dataset	Result findings
24	Our objective is to develop a Global-Part Convolutional Neural Network (GP-CNN) model that treats the fine-grained local information as well as the global context information equally well	Part Convolutional Neural Network (P-CNN), Global-Part Convolutional Neural Network (GP-CNN)	ISIC 2016 ISIC 2017 SLC	Researchers have tested the suggested method on the ISIC 2016 SLC dataset and found that it achieves state-of-the-art classification performance without external data (AP = 0.718, AUC = 0.926)
25	Automatic melanoma detection using dermoscopy image	Deep learning, transfer learning	Mole Map HAMMoleMAp	Image Net without fine-tuning surpasses it by 0.01 percent for melanoma vs benign categorization. That's because MD (Multidimensional) photos supply lots of clean text for categorising

Table 4. Results comparison of existing skin lesion detection

Ref No	Methology	ACC	SEN	SPEC	AUC	RECALL	F-score
[2]	SNN	74.1	87.1	66.8	74.8	–	–
[4]	SPBL	67.8	–	–	68.5	65.7	66.2
[7]	IM-CNN	95.1	83.5	93.2	97.8	–	–
[10]	DCNN	86.81	–	–	85.2	–	–
[12]	DRA	86.8	–	–	92.2	86.8	87.1
[16]	DCNN	92	81	97	–	–	–

Asymmetry means that one half of the mole does not match the other in the ABCD melanoma detection criteria. The mole's border and margins are not smooth. The mole is multicolored, hence the C. The letter D denotes a larger diameter or width than a pencil eraser. Compared to a normal mole, E stands for evolving size, shape, and colour. The Table 4 summarizes the many methods for detecting Melanoma skin lesions.

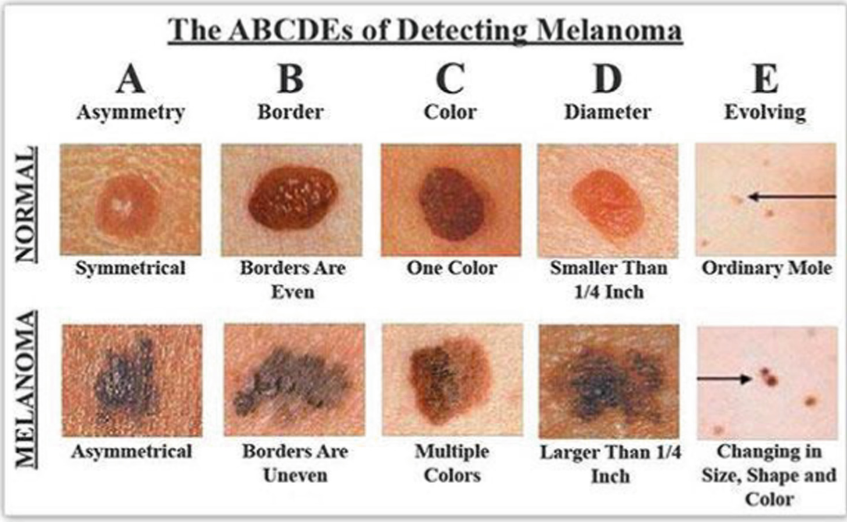

Fig. 2. ABCDE of detection melanoma

7 Skin Lesion Segmentation in Melanoma Skin Cancer

Numerous approaches are already developed and applied for the efficient segmentation of skin lesions. Particularly in recent times, the deep learning approach, Convolutional Neural Network (CNNs) has achieved veritably successful results in segmentation of skin lesions Still, CNNs accepts low- resolution images for dwindling the number of computations and parameters in the network. This situation may lead to the loss of some important features in the image. Table 5 describes the methodology and approaches used to segment melanoma skin lesion.

Table 5. Results comparison of existing skin lesion segmentation

Ref No	Dataset	JA	DI	AC	SE	SP	TJI	JSI	DSC	ACCC
[3]	ISIC-2017	80.4	87.8	94.7	87.4	96.8	–	–	–	
	PH2	89.4	94.2	96.5	96.7	94.6	–	–	–	
[22]	ISIC 2017	0.849	0.911	0.956	0.888	0.985	–	–	–	
[1]	ISBI2017	–	–	–	90.6	96.2	78.5	82.5	89.6	95.7
	1SIC2018	–	–	–	94.2	94.1	80.4	84.4	90.8	94.7
[9]	ISBI2016	88.38	93.62	–	–	–	–	–	–	–
	ISBI2017	77.26	85.325	–	–	–	–	–	–	–

8 Classification in Melanoma

From once exploration in this field, it's apparent that CNN has an extraordinary capability to perform skin lesion bracket in competition with professional dermatologists (Table 6). In fact, there have been cases where CNN has outperformed professional dermatologists as well in Fig. 3. Skin lesions can be classified in two ways, according to CNN. A CNN is utilized to extract picture points in the first case, while another classifier classifies the images within seconds. In other circumstance, CNN is used to conduct end-to-end literacy. Scrape literacy and pretrained model literacy are two types of scrape literacy. To overcome the problem of overfitting, more photographs are essential to train the CNN from scraping. Training CNN from scrape is more difficult due to the small number of skin lesion images necessary for training. A better method is to learn from a pre-trained system which is Transfer Literacy (TL). The concept attribute is introduced to the trained model by TL, which helps the model learn better with little input.

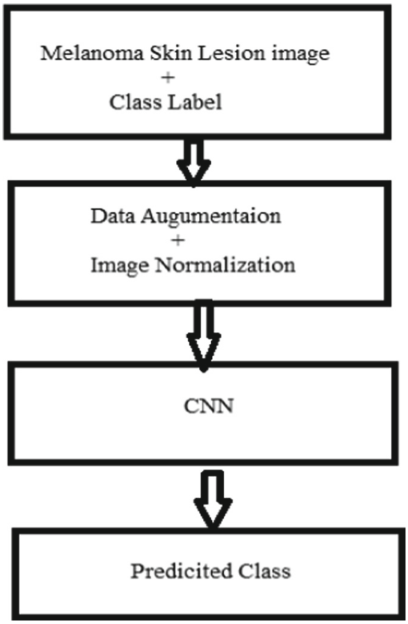

Fig. 3. Classification of melanoma skin lesion

Table. 6. Results comparison of existing skin lesion classification

Ref no	Method used	Model/dataset used	Sensitivity	Specificity	F-score	AUC	ACC	BMA
[5]	CNN	IncepV3	64.0	93.1	75.5	–	–	–
		Dense	67.8	93.1	75.5	–	–	–
		SE-RX50	66.9	93.2	73	–	–	–
[6]	UNIT-VISE	HAM10000	97.23	98.94	97.33	–	98.05	–
[8]	ARL-CNN50	ResNet50	0.658	0.896	–	0.875	0.850	–
		ResNet14	0.615	0.818	–	0.777	0.778	–
[13]	CNN	DenseNet201-SLA-STYLEGAN	0.856	–	–	0.964	–	0.996
[15]	MTFL	ISIC2017	62.4	91.9	–	87.9	86.2	–
[17]	DeepCNN	ResNet152	97.04	97.23	–	–	87.42	–
[23]	FRCN	DenseNet	97.5	96.5	89	–	95.5	–

9 Conclusion

Deep learning's capacity to handle vast amounts of features makes it useful for unstructured data. We analyzed more current papers and found that most researchers employed neural network techniques with deep learning. For example: Convolutional Neutral Networks and Recurrent Neural Networks. In a CNN, the hidden layers don't necessarily share their output with the next layer (known as convolutional layers). Automated feature extraction from images using deep learning. They can learn what to search for in images by analyzing many images. As shown above, staggered Profound Learning models are particularly useful in distinguishing confounded data from input images. Convolutional neural networks can also drastically reduce computation time by utilizing GPUs, which many do not use. In this way, the grouping model can recognize the image. Keras has inbuilt capacities that make it simple to customize and make a neural organization with CNN design. We plan to create our own Convolutional Neutral Network for Melanoma Order with our own rendition of turns.

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