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SKIN CANCER DETECTION USING DEEP LEARNING MODELS

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Abstract—**In the United States, skin disease is a not kidding general medical condition, with north of 5,000,000 new cases analyzed every year. The two most incessant kinds of skin disease are melanoma and non-melanoma skin malignant growths. Melanoma is otherwise called harmful melanoma. Melanoma is the nineteenth most predominant malignant growth in people the same. It's the deadliest sort of malignant growth; by 2020, the public event of melanoma disease will have expanded to 5.14 guys and 3.98 females analyzed for each 100,000 people. Be that as it may, this is as yet a little level of the worldwide melanoma rate. With a pervasiveness of 6.2, guys in the East seemed to have the most noteworthy pace of nonmelanoma skin disease. In the Western Pacific district, nonmelanoma skin malignant growth is found in 225.4 percent of men and 68.6 percent of ladies. Clinical preliminaries have been basic in finding what works and what doesn't in that frame of mind of different tumors. More clinical preliminaries are required in India, as per specialists, both for patients who have attempted any remaining treatments and need to take a stab at a genuinely new thing, as well as to assist with creating fixes or arrangements that turn out best for the Indian populace. This spurs us to make an answer that could save a large number of lives by means of early location of skin disease utilizing different profound learning models. The objective of this paper is to foster a framework for recognizing skin disease that utilizes different CNN models to characterize various sorts of skin malignant growth and help in early diagnosis.**

Keywords—Skin cancer · Deep learning ·skin Cancer detection ·skin Cancer diagnosis · Convolution neural network · CNN· Melanoma

1. Introduction

Skin cancer has been recognized since the early 1800s. Rene Theophile Hyacinthe Laennec, a French physician who invented the stethoscope, discovered it. [1]. Skin cancer accounts for one out of every three cancers, according to the World Health Organization. [2]. Skin cancer is usually treatable if identified early, but it can be difficult to cure and even fatal if not caught early. [3] A painful, itchy, or burning lesion on the affected area is one of the symptoms of skin cancer. On the surface, a large brownish patch with darker speckles. A bleeder or mole that changes color, size, or texture. A little lesion with an irregular border with portions of red, pink, white, blue, or blue-green. Sun-exposed areas of the body, such as the head, face, lips, ears, neck, chest, arms, and hands, as well as the legs in women, are the most common sites for skin cancer. It can also affect sections of your body that are rarely exposed to sunlight, such as your palms, the area under your fingernails or toenails, and your genital area. The head, face, lips, ears, neck, chest, arms, and hands, as well as the legs in women, are the most common sites for skin cancer It can also appear on parts of your body that aren't exposed to the sun all that often, such as your hands, under your fingernails or toenails, and your genital area. People of all skin tones, especially those with darker complexions, are susceptible to skin cancer. The three most frequent types of skin cancer are basal cell carcinoma, squamous cell carcinoma, and melanoma. The survival rate of skin cancer patients who are diagnosed early is over 95%, demonstrating the importance of early identification in the treatment of such diseases. [4] Tumor cells are classified as benign or malignant. Benign cells have a well-defined structure and do not expand or spread, but malignant cells can rapidly develop and spread. [5]. Cancer cells are treated with chemotherapy, radiation, and surgical intervention because they are lethal. Depending on gender and age, tumours may be distributed differently. Depending on the species and organs affected, cancer expresses itself in a variety of ways. As a result, early detection is critical in the treatment of all cancer patients, including those with skin cancer. [6] Deep learning architectures have recently shown an active interest in medical research, and this trend is predicted to continue. [7] In this scenario, artificial intelligence-enabled software might be used to diagnose skin cancer by analyzing photos to determine whether or not a person is affected. This proposed technique is aimed to unavoidably distinguish skin cancer using a digital image, despite the use of numerous convolutional neural networks to maximize correctness. The skin cancer photos were saved as part of a study to see if they might predict whether or not someone had cancer. The model can accurately predict the presence of skin cancer, according to this study,

which integrates many literature reviews with several deep learning models and statistical analysis. A range of surveys, as well as techniques and data analysis, are included in this publication.

RELATED WORKS

Artificial intelligence technology is one of the most frequently discussed issues in the medical literature. In this paper, a novel categorization technique is proposed that could allow for automatic and rapid skin pre-analysis in the majority of cancer cases. Details of a few studies undertaken on this topic are published in the literature.

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The paper by Pratik Dubal et al [8] has researched skin cancer classification. The ABCD rule is used to extract the features. They divided the lesions into three types: benign, intermediate, and malignant. Melanocytic Nevi, Seborrheic Keratoses, and Acrochordon are examples of benign lesions, whereas Melanoma, Basal Cell Carcinoma (BCC), and Squamous Cell Carcinoma are examples of malignant lesions (SCC). The dataset was separated into three sets: training, testing, and validation, with each set consisting of 80%, 10%, and 10% of the total dataset. A neural network was trained to classify lesions with an accuracy of 76.9% on 463 images.

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Mehmet Baygin et al [9] distributed a paper about his examination advantages in defeating difficulties with programmed skin disease finding. The dataset contains 3297 photographs separated into two classifications. A model is fostered that depends on programmed multi-facet textural and profound elements. Staggered combination include blend utilizing discrete wavelet change (DWT), neighborhood stage quantization (LPQ), nearby paired design (LBP), pre-prepared DarkNet19, and DarkNet53 is used to make highlights for skin malignant growth photographs. A local part examination with a limit esteem is utilized to pick the main 1000 elements (NCA). The main 1000 highlights are characterized utilizing the 10-overlap cross-approval method. Ten times cross-approval is utilized to come by results, with 91.54 percent order precision, utilizing the recommended pyramidal mixture highlight generator and NCA selector-based model. Partition proportions of 90:10, 80:20, 70:30, 60:40, and 50:50 is additionally utilized in preparing and testing, with the 90:10 detachment proportion having the most noteworthy order pace of 95.74 percent.

In this review, S. P. Maniraj and P. Sardar Maran [10] offer a mixture deep learning technique that utilizes sub-band combination of 3D wavelets. In the principal phase of the HDL approach, basic middle sifting is utilized to eliminate undesirable data like hair and commotion. In the subsequent stage, a subband combination procedure is utilized to recuperate textural data from the dermoscopic picture utilizing the 3D wavelet change. In the last stage, the HDL approach is applied to accomplish multiclass grouping utilizing the combined sub-band. Customary classifiers like KNN, SVM, and BoF, as well as other profound learning calculations, are looked at against the HDL approach's exhibition. The HDL strategy beats methods that depend on customary classifiers and worldly information like shape, line, and variety. Other recurrence area investigations, like FFT, DCT, and NSCT, are beated by 3D-DWT. The HDL approach's presentation discoveries on the PH2 information base show that it is more powerful at recognizing typical and neurotic skin pictures. The HDL approach has a precision of 99.33%Ulzii-Orshikh Dorj et al [11] The authors concentrate on employing ECOC SVM and deep convolutional neural networks to classify skin cancer. The RGB photographs were gathered from the internet. For better results, the photos have been cropped to reduce noise. The features are extracted using a pre-trained Alex Net convolutional neural network model. Skin cancer is classified using an ECOC SVM classifier. The greatest values of average accuracy, sensitivity, and specificity are 95.1 (squamous cell carcinoma), 98.9 (actinic keratosis), and 94.17 (squamous cell carcinoma), respectively, according to the implementation result. 91.8 (basal cell carcinoma), 96.9 (squamous cell carcinoma), and 90.74 (melanoma) are the lowest average values in these measures

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The authors of paper of Arslan Javaid et al [12] were A technique for classifying and sectioning skin injuries as harmless or dangerous has been made utilizing picture handling and AI. Another strategy in view of mean qualities and standard deviation of pixels is proposed for contrast extending of dermoscopic pictures. The picture is therefore sectioned utilizing the OTSU thresholding strategy. From that point forward, highlights incorporate dim level Co-event Matrix (GLCM) highlights for surface distinguishing proof, the histogram of situated inclinations (HOG) item, and variety ID highlights are removed from the portioned pictures. Hoard attributes are diminished utilizing head part examination to limit dimensionality (PCA). Classifiers like Quadratic Discriminant, SVM (Medium

Gaussian), and Random Forest are utilized for characterization. The most extreme degree of exactness is accomplished with the Random Forest classifier. The recommended approach with the Random Forest classifier has a characterization exactness of 93.89 percent on ISIC-ISBI 2016.

R Raja Subramanian and partners [13] Based on past clinical imaging information, the creators are utilizing Convolutional Neural Networks (CNN) to recognize and classify malignant growth sorts. Building a CNN model to distinguish skin malignant growth with an exactness of >80%, keeping the misleading negative rate in the expectation beneath 10%, accomplishing an accuracy of >80%, and performing information perception are a portion of their review goals. There are 16 levels in the CNN model involved here for skin disease order. Accuracy was 0.818642, Recall was 0.80509, and F-score was 0.82797 for the creators, with preparing exactness of 83.11 percent and testing precision of 83.04 percent (utilizing the first HAM10000 dataset).

Khalid M. Hosny and partners [14] This review proposes a mechanized skin injury characterization strategy. This strategy utilizes a pre-prepared profound learning network as well as move learning. Move learning is used to classify three distinct injuries by supplanting the last layer with a SoftMax, as well as tweaking and information increase (melanoma, normal nevus, and abnormal nevus). The recommended model is prepared and assessed utilizing the ph2 dataset. The presentation of the suggested strategy is surveyed utilizing the notable quotative measurements of exactness, responsiveness, particularity, and accuracy, yielding 98.61 percent, 98.33 percent, 98.93 percent, and 97.73 percent, separately.

Soniya Mane et al [15] In this work, the images of skin is initially pre-processed. The input image is transformed to grayscale with this system. In the preprocessing step, a Gaussian filter was utilized to remove hairs. Following the above processing, An image segmentation technique is used to segment the disease portion, which is then followed by feature extraction, which extracts unique features from the segmented lesion. The skin image is identified as normal skin or melanoma skin cancer using support vector machine classification after feature extraction. The SVM linear kernel classifier has great sensitivity, specificity, and accuracy. Sensitivity is 93.33 percent, specificity is 90.90 percent, and accuracy is 92.30 percent.

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METHODOLOGY

A. *Dataset description*

The HAM10000 database [16] consists of dermoscopy photos of common pigmented skin lesions from a variety of sources. 6705 photos of Melanocytic neviproblem, 1113 photos of Melanoma,1099 images of skin problem Benign keratosis, 514 images of problem Basal cell carcinoma, 327 images of Actinic keratosis, Vascular Lesions related 142 photos, and Dermatofibroma are among the skin cancers represented in the dataset (142 images). The dataset's 10,015 photographs were used to construct a training set (8912 images) and a validation set (8912 images) (1103 images). The approval information is comprised of unique cases from the dataset (i.e., Cases in which various pictures were connected to a similar injury id were eliminated from the approval cycle). Thus, for a fair-minded assessment of the model's presentation, both the preparation and approval sets should contain an assorted determination of pictures.

B. *CNN architecture*

Convolution is a mathematical function that expresses how one function's shape is influenced by another's shape. It's a form of linear operation in which two components are multiplied to create a third function that expresses how the shape of one function is influenced by the shape of the other... Simply multiplying two matrices yields an output that can be used to extract image data. CNN's basic architecture is as follows

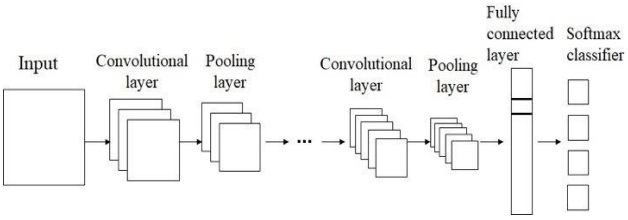

Fig 1. Architecture of CNN

Convolution Layer: The formula for the feature map calculated by the convolution operation is as follows:

$$s[t] = (x*w)[t] = \Sigma\, x[a]\, w[a+t] \qquad (1)$$

Were,

s represents the feature map
x represents the input and
w represents the kernel

The dimension of the feature map is calculated using

$$(W-F+2P)/S+1 \qquad (2)$$

Here W represents the width of the input layer

F represents Feature detector size
S represents Stride
P represents Zero Padding on the image

Activation Layer: The softMax activation function is used here, and the formula is given below,

$$Softmax(Z_i) = exp(z_i) / \Sigma_j exp(z_j) \quad (3)$$

Z denotes the values from the neurons of the output layer

Classifier: We employ multi-class cross-entropy, a type of cross-entropy in which the output is a single-hot encoded vector.

$$Categorical\ cross\ entropy = - log\ q(x) \quad (4)$$

Where x is the class or the category and q(x) represents the probability.

Output Layer: The size of the output in the CNN layer is determined as

$$input\ size-(filter\ size-1) \quad (5)$$

Here the input size is 28*28*1 and the filter size is 2*2. However, because the size of a Convolutional network's input images cannot be smaller than the input, padding is used.

$$Input\ size + 2 * padding\ size-(filter\ size-1) \quad (6)$$

is used to compute padding. Here the input size is again 28*28*1, the filter size is 2*2, and the padding size is 3*3.

C. Convolution Neural Network with three convolutional Layers

The size of the CNN model in a CNN with three convolutional layers must be set to 28 * 28 * 1, which matches the size of the skin cancer data input. This size is fed into the first layer as an input. The training time and the number of parameters must be lowered to make the model more efficient. For this performance gain, the max-pooling approach is used in the second layer., hence the term Max Pooling 2D layer. A pooling window of size 2*2 is utilized to accomplish this. The output of the second layer may cause overfitting to the training data, hence the dropout layer is used to solve this problem. In a different pattern, this dropout layer inhibits 20% of the neurons The procedure is carried out by the Dense layer, also known as the completely connected layer. This is the final output layer; it handles 1D vectors, whereas the prior layer's output is in 3D. As a result, the 3D outputs are flattened to 1D before being processed further. On top of that, the remaining two layers of 2D vectors are applied. In addition, we add a second Drop out layer, however, this time just 30% of the neurons are inhibited. The input is now provided to the categorical cross-entropy, which is utilized to create a multi-class classifier. For each input, the SoftMax activation layer calculates the probability value of each class and the maximum probability of this layer, which is regarded as the model's output. The SoftMax function, together with the Adam Optimizer, is used as a loss function while constructing the model. The error rate is calculated using the cross-entropy loss function. To deal with the discrepancy between expected and original values, the Adam Optimizer is utilized. This optimizer modifies the weight based on the loss function's derivative, producing a more accurate model.

D. Convolutional Neural Network with four convolutional Layers

Similarly as with prior models, the CNN model's size is set to (28*28*1 size) to match the configuration of the dermoscopy pictures. This can be molded more than once bypassing the contention to the main layer as the information shape = (28*28*1 size). The Conv2D layer is the model's initial layer, which involves extracting features from input images using a convolution filter and producing a feature map. This model makes use of a 3 x 3 feature map. The Max Pooling 2D layer is the second layer, and it significantly decreases the time it takes to train the model. It also minimizes the number of parameters by employing a 2 x 2 pooling window. Overfitting must be avoided. As the third layer, we add a Dropout layer, which is an effective regularizations approach. The Drop out layer, an efficient regularization approach, addresses the problem of overfitting. This layer randomly inhibits 20% of the neurons. The densely linked layers, also known as the fully connected layer, receive the output of the dropout layer as input. The dense layers were unable to process the dropout's output because it is 3D data. As a result, the data is flattened to 1D before the other two dense layers are applied. The odds of each input class are calculated using the SoftMax activation function. The output of the model for the specified input class is the maximum probability value. We used SoftMax as the loss function for assembling the model since it could efficiently handle the multi-class classification of many skin cancer. To update the weights, the Adam optimizer is utilized to backpropagate the error. The optimizer receives the error date from the cross-entropy loss function.

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E. DCNN

The deep CNN is a model with many layers that are concealed from view. In this technique, we used ten convolution layers, four maximum pooling layers, and one fully connected layer for classification. Conv2D, Max Pooling 2D, drop out layer, and Dense layer

are the model's sequential layers, as they were in the previous cases. We introduce a drop-out layer at the last max-pooling layer, which regularizes the output, to alleviate the issue of overfitting in the d-CNN. As a result of the dropout, around 25% of the neurons are randomly blocked. Along with the classifier, the SoftMax activation function is utilized to capture the maximum probability for each class. The softmax function is utilized as a loss function for multi-class categorization of various cancer in the skin taken as input when compiling. The cross-entropy loss function is used to calculate the difference between actual and predicted values, and the Adam optimizer modifies the weights based on the measured error rate. This procedure's accuracy has greatly increased.

RESULT ANALYSIS

In this exploration, we utilized insightful techniques to look at the capacities of a few convolutions layer models on dermoscopic pictures of skin disease and assembled a skin malignant growth location picture classifier model in view of convolution layers. Our model partitions dermoscopic pictures into seven classifications and table 1 addresses the precision of various models involving different convolution layers for dermoscopic skin pictures. The accompanying graphs portray the (precision versus epoch)

TABLE 1 : ACCURACY AND LOSS RATE OF DIFFERENT MODELS

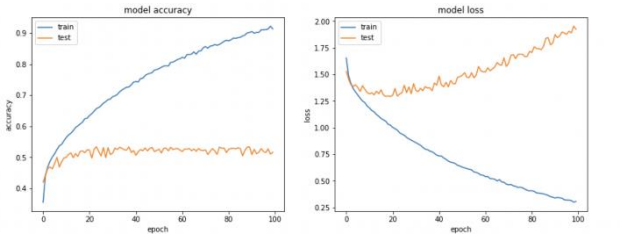


Fig 1. Accuracy and loss Variation for each input class for CNN

Model	Accuracy	Loss	Validation Loss	Validation Accuracy
CNN with II convolutional layer	91.35	3.069	19.250	51.63
CNN with III convolutional layer	95.13	1.358	36.388	56.03
CNN with IV convolutional layer	96.76	0.948	35.165	56.78
DCNN	98.13	0.593	21.054	65

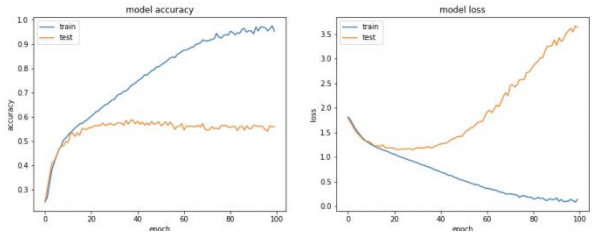


Fig 2 Accuracy and loss Variation for each input class for 3-layered CNN

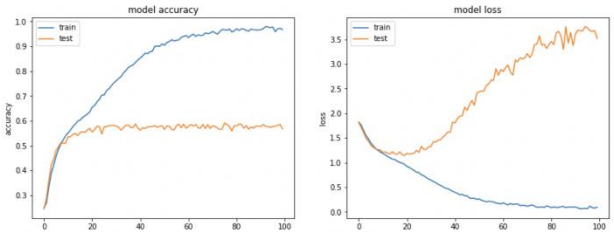
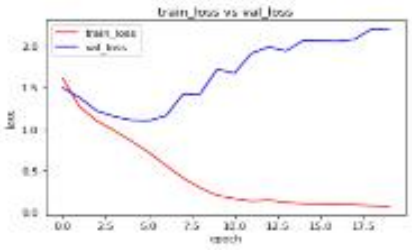


Fig. 3. Accuracy and loss Variation for each input class for 4-layered CNN



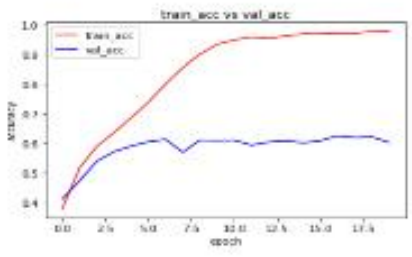


Fig 4 Accuracy and loss variation for each output class for dcnn

There has been a tremendous improvement in accuracy. as shown in the table. As the number of CNN layers grows, the loss, as well as the validation loss, reduces. The DCNN model has the maximum accuracy, and the training dataset, as well as the dropout layers, can be fine-tuned to further improve it. This updated model has the potential to be used in the previously listed applications.

The accuracy and loss parameters for both the training and testing datasets have been presented below as a result of the analysis

CONCLUSION AND FUTURE WORKS

The results show that the accuracy improves considerably as the number of CNN layers increases. Furthermore, DCNN outperforms CNN's other different layers. In this paper, a survey and analysis of the many types of CNN architectures, as well as the usage of dcnn for skin cancer image classification, is covered, along with the accuracy of findings and performance. A brief overview of Melanoma's operation and detection is provided, which is essential for classifying normal and malignant skin cells and tailoring the architecture of CNN and DCNN models to meet the problem correctly. Adjusting the learning rate decay schedule, as well as the location and probability of dropout, are instances of fine-tuning. Future development in the skin cancer detection system could be more accurate and efficient if the system could be implemented as a standalone mobile application, making it more reliable and practical

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