|| Volume 6 || Issue 5 || May 2021 || ISSN (Online) 2456-0774
INTERNATIONAL JOURNAL OF ADVANCE SCIENTIFIC RESEARCH AND ENGINEERING TRENDS

DETECTION OF SKIN CANCER USING CNN ALGORITHM

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Abstract: Skin cancer is one of the deadliest types of cancer. If it is not diagnosed and treated early on, it is likely to spread to other areas of the body. It is primarily caused by abnormal skin cell development, which occurs often when the body is exposed to sunlight. The Surveillance Furthermore, identifying skin malignant development in its early stages is an expensive and difficult process. It is graded according to where it grows and what type of cell it is. The classification of lesions necessitates a high level of precision and recall. The MNIST HAM-10000 dataset containing dermoscopy images will be included in this article. The aim is to propose a method that uses a Convolution Neural Network to diagnose skin cancer and classify it into various groups. Image recognition and a deep learning algorithm are used in the diagnosis process. The noise and picture resolution were removed from the dermoscopy shot of skin cancer that was taken. Using different image augmentation methods, the image count may also be improved. Finally, the Transfer Learning approach is used to improve the image recognition accuracy even further. The weighted average Precision of our CNN model was 0.88, the weighted average Recall was 0.74, and the weighted f1-score was 0.77. The accuracy of the transfer learning method using the ResNet model was 90.51 percent.

Keywords: Skin Cancer, Skin lesion, Deep learning, CNN.

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I INTRODUCTION

In 2018, there were over a million cases of skin cancer worldwide [1]. One of the fastest-growing diseases on the planet is skin cancer. The susceptibility to ultraviolet radiation released by the Sun is the primary cause of skin cancer. Early diagnosis of skin cancer is critical with the scarce services available. In general, for skin cancer prevention strategy, accurate diagnosis and identification viability are crucial. And dermatologists face difficulty in detecting skin cancer in the early stages.

Deep learning has been widely used in both supervised and unsupervised learning challenges in recent years. Convolution Neu- ral Networks (CNN) is one of these models that has outperformed all others in object detection and classification tasks. By mastering highly discriminative features when being practiced end-to-end in a controlled manner, CNNs remove the need for manually handcrafting features.

Recently, Convolutional Neural Networks (CNNs) have been used to classify Lesions in skin cancer In the classification of skin cancers, some CNN models have outperformed qualified human specialists. Several approaches, such as transfer learning, are available.The performance of these simulations has increased even further thanks to the use of massive datasets.

VGG-16 is a convolutional neural network that has been trained on over a million images. images from the ImageNet collection The framework has 16 layers which can be configured in a variety of ways. Pictures are divided into 1000 different categories, such as console, mouse, pencil, and various animals. As a result, the machine has studied detailed component representations for a variety of objects.a broad range of images The image information scale on the system is 224 by 224 pixels. The definition of the model In ImageNet, a dataset with over a million images, it achieves 92.7 percent top-5 test precision. There are 14 million pictures in 1000 schools.

In this paper, we have generated a CNN model that analyses the skin pigment lesions and categorizes them using a publicly available dataset and a variety of methods. techniques for deep learning By using CNN and transfer learning models, we were able to increase classification accuracy. The HAM-10000 dataset, which is freely available, was used to validate our model.

II LITERATURE SURVEY

CNNs have been widely used in medical image analysis, image recognition, and other fields [2]. In the area of microscopic picture classification, CNNs have already shown impressive results, such as human epithelial 2 cell image classification [3], diabetic retinopathy fundus image classification [4], cervical cell classification [5], and skin cancer identification [6-9].

The first systematic study on classifying skin lesion diseases was proposed by Brinker et al. [10]. The writers concentrate on the use of CNN for skin cancer classification. The study further addresses the difficulties that must be overcome in order to complete the classification process. Han et al. suggested a clinical image-based classifier for 12 related skin disorders in [11]. They used 19,398 training images from the Asan dataset, the MED-NODE dataset, and atlas site images

|| Volume 6 || Issue 5 || May 2021 || ISSN (Online) 2456-0774
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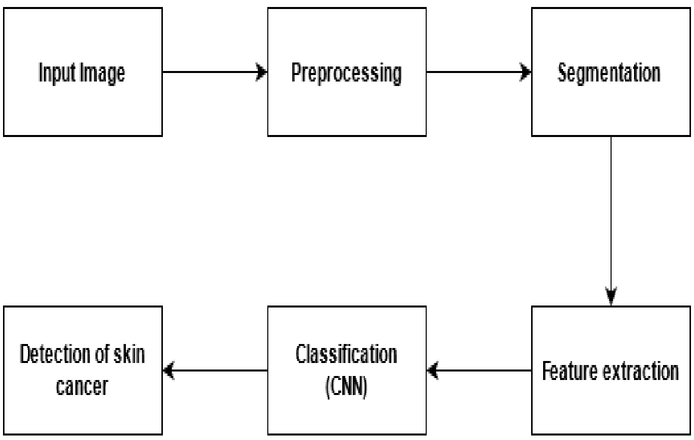
to fine-tune a ResNet model. This study does not take into account patients of various ages.

The first comparison of CNN with an international association of 58 dermatologists for skin cancer assessment was proposed by the authors in [12]. The majority of dermatologists The CNN outperformed them. The authors concluded that, regardless of any physicians' opinions, They could benefit from the image classification provided by a CNN. Google's search engine Dermoscopic images were used to train and test the Inception v4 CNN architecture. as well as the corresponding diagnoses Marchetti et al. [13] used 100 randomly chosen dermoscopic photographs in a cross-sectional sample (50 melanomas, 44 nevi, and 6 lentigines)

An international machine vision melanoma challenge dataset (n = 379) was used in this research. For the classification function, the authors constructed a fusion of five approaches. The authors of [14] used 7895 dermoscopic and 5829 close-up photographs of lesions to train a CNN-based classification model. Between January 1, 2008, and July 13, 2017, these photographs were excised at a primary skin cancer center. Furthermore, the model was tested on a sample of 2072 unknown cases and the findings were compared to those of 95 individual raters who were medical professionals.

The majority of current research focuses on binary classification, such as whether the cancer is melanoma or not, and only a limited amount of study is done on classification of general images. However, their outcome isn't ideal. Deep learning and neural network architectures are now used in skin cancer disease identification and classification algorithms.

System Architecture



III METHODOLOGY

This Section will emphasis over the methodology adopted for the classification task. Over all steps of the methodology is shown in figure 1.

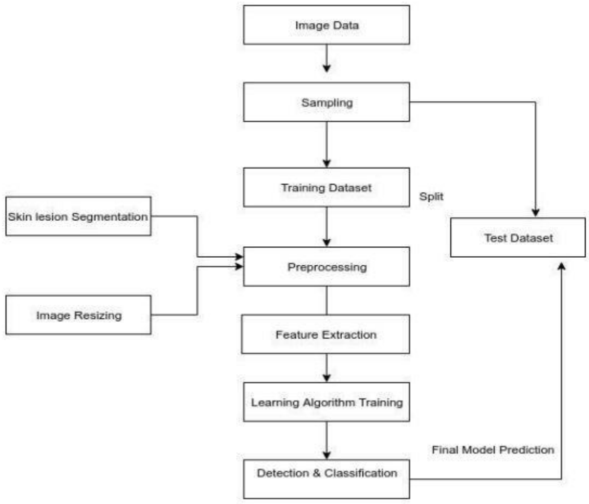
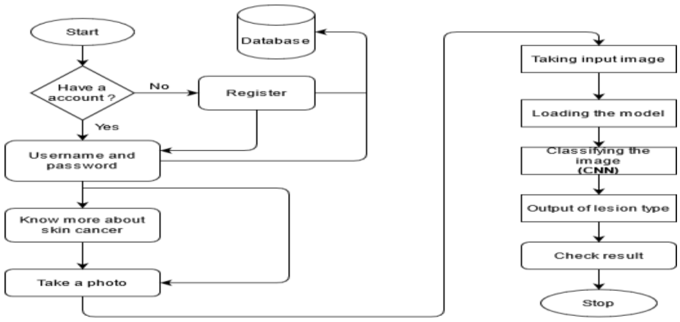


Fig. 1. The Flowchart of the methodology implemented.



We used the MNIST HAM-10000 Skin Cancer dataset, which is available on kaggle [15,16]. It includes 10015 photographs of skin pigments grouped into seven categories. The dataset contains enough images to be used for a variety of tasks such as image retrieval, segmentation, feature extraction, deep learning, and transfer learning, among others.

Preprocessing

Before being fed into the model, the data had to be washed and ordered. The data is, however, heavily skewed, with the lesion category 'melanocytic nevi' accounting for more than half of the overall dataset. To improve the learnability of the network, we used many pre-processing networks. We used Data Augmentation to prevent data from being overfit. By varying the translation, rotation, and zooming of the files, we were able to make multiple copies of the existing dataset. In addition, we used Histogram Equalization to improve the contrast of skin lesions in this article.

Method

For the classification task, Convolutional Neural Networks and Transfer Learning approaches are used. Deep learning models pre-trained on the ImageNet dataset were used for Transfer learning. It contains a little more than 14 million labelled photographs divided into over 20,000 categories. These pre-trained models are then further trained on the HAM10000 dataset by inserting additional layers and freezing some of the initial layers. To compare the results, we used various learning algorithms such as XGBoost, SVM, and Random Forest Algorithms to perform the classification task in the HAM10000 dataset.

Convolution Neural Network

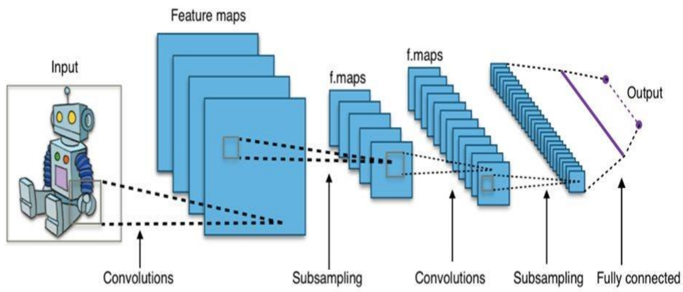
Biological mechanisms influenced convolutional neural networks. The communication pattern between neurons in these networks parallels the organization of the visual cortex in animals. The receptive field is the response of a single cortical neuron in a limited area of the visual field. Different neurons' receptive fields partly overlap, allowing them to occupy the whole visual field. To assemble its architectures, CNN uses three levels of neural layers: Convolutional, Pooling, and FullyConnected.

Convolutional Layer: The convolutional layer is the most important layer in CNN. The product of the output layer is obtained from the input by filtering in special conditions in this layer. This layer is made up of neurons that are shaped like cubical blocks.

Pooling layer: After each convolution layer, the pooling layer performs the next operation. These layers are used to keep the scale of the neurons as small as possible. These are tiny rectangular grids that take a small slice of the convolutional layer and filter it to produce a result from that block. The most widely used layer is peak pooling, which retrieves the block's maximum pixel.

Completely connected layers: A fully connected layer in a convolutional neural network (CNN) is created by the connection of all preceding neurons. Since it is completely connected, like an artificial neural network, it reduces spatial information. It is made up of neurons that start at the input and end at the output.

Transfer Learning



Transfer learning is a methodology in which a concept that has already been learned is applied to a new dataset. If there isn't enough data to accurately train the algorithm, this method is used. In these instances, a new model is used that has already been trained on a particular large dataset. We used some of the pre-trained models from the ImageNet dataset, which contains millions of images aligned with 1000 groups. These models are then supplemented with various untrained layers and trained on the HAM10000 dataset. Figure 2 depicts the architecture of the models used, specifically VGG16.

IV CONCLUSION

The suggested method takes the approach of extracting features first, and using those features to train and validate the transfer learning model. According to the As a result of our observations, we have come to the conclusion that the Transfer Learning process should be used. to the HAM10000 dataset in order to improve skin cancer lesions classification accuracy. We also discovered that the ResNet model, which is pre-trained in the ImageNet Dataset, performs well. The effective classification of cancer lesions in the HAM1000 can be extremely useful.

We have discovered that in the HAM10000 dataset, learning algorithms such as Random Forest, XGBoost, and SVMs are ineffective for classification tasks. As a result of these findings, future research will focus on improving prediction results and classification accuracy.

REFERENCES

[1] Ferlay, J., et al. "Estimating the global cancer incidence and mortality in 2018: GLOBOCAN sources and methods." International journal of cancer 144.8 (2019): 1941-1953.

[2] Kasinathan, Gopi, et al. "Automated 3-D lung tumor detection and classification by an active contour model and CNN classifier." Expert Systems with Applications 134 (2019): 112-119.

[3] Gao, Zhimin, et al. "HEp-2 cell image classification with deep convolutional neural networks." IEEE journal of biomedical and health informatics 21.2 (2016): 416-428.

[4] Wang, Pin, et al. "Automatic cell nuclei segmentation and classification of cervical Pap smear images." Biomedical Signal Processing and Control 48 (2019): 93-103.

[5] Sharma, Sunil, Saumil Maheshwari, and Anupam Shukla. "An intelligible deep convolution neural network based approach for classification of diabetic retinopathy." Bio-Algorithms and Med-Systems 14.2 (2018).

[6] Hosny, Khalid M., Mohamed A. Kassem, and Mohamed M. Foaud. "Classification of skin lesions using transfer learning and augmentation with Alex-net." PloS one 14.5 (2019): e0217293.

[7] He, Xinzi, et al. "Dense deconvolution net: Multi path fusion and dense deconvolution for high resolution skin lesion segmentation." Technology and Health Care 26.S1 (2018): 307-316.

[8] Harangi, Balazs. "Skin lesion classification with ensembles of deep convolutional neural networks." Journal of biomedical informatics 86 (2018): 25-32.

[9] Brinker, Titus J., et al. "Deep learning outperformed 136 of 157 dermatologists in a head-to-head dermoscopic melanoma image classification task." European Journal of Cancer 113 (2019): 47-54.

[10] Brinker, Titus Josef, et al. "Skin cancer classification using convolutional neural networks: systematic review." Journal of medical Internet research 20.10 (2018): e11936.

[11] Han, Seung Seog, et al. "Classification of the clinical images for benign and malignant cutaneous tumors using a deep learning algorithm." Journal of Investigative Dermatology 138.7 (2018): 1529-1538.

[12] Haenssle, Holger A., et al. "Man against machine: diagnostic performance of a deep learning convolutional neural network for dermoscopic melanoma recognition in comparison to 58 dermatologists." Annals of Oncology 29.8 (2018): 1836-1842.

[13] Marchetti, Michael A., et al. "Results of the 2016 International Skin Imaging Collaboration International Symposium on Biomedical Imaging challenge: Comparison of the accuracy of computer algorithms to dermatologists for the diagnosis of melanoma from dermoscopic images." Journal of the American Academy of Dermatology 78.2 (2018): 270-277.