International Journal of Scientific Research in Engineering and Management (IJSREM)
Volume: 07 Issue: 06 | June - 2023 SJIF Rating: 8.176 ISSN: 2582-3930

SKIN CANCER DETETCTION USING IMAGE PROCESSING

Ms.Kumud Sachdeva
Dept.of CSE
Chandigarh University
Kumud.cse@cumail.com

Nitish Kumar
CSE 514/B
Chandigarh University
Nitishrao4026@gmail.com

Hobokela Asajile Mwakisisile
CSE 514/C
Chandigarh University
hobokelamwakisisile@gmail.com

Neha Kumari Nandini
CSE 514/A
Chandigarh University
nehakumarinandini@gmail.com

Abstract :

Skin cancer is the uncontrolled growth of abnormal skin cells in the body. It occurs when the damage to skin cells—most often caused by ultraviolet radiation from sunshine or tanning beds— causes skin cells to multiply rapidly and form malignant tumours. At the early stage, it can be treated and one can be free from cancer, but there is a risk of no treatment at the late stage. which has led to a high motility rate, and due to its expensive treatment people opt not to test.

to develop a deep-learning machine system that can be able to clarify cancer victim skin picture from normal skin by processing the image sample provided as a sample. Using deep learning algorithm implementation where images of victims and the data of victims are uploaded as data of the modal and the system sorts out cancer and normal. The technique used was CNN

(Convolutional Neural Network) for the Through this modal system, we can build a deep learning modal to predict skin cancer in human

Keywords: DNN (Deep neural networks), CNN (convolutional neural network modal),et al(and others)

1.Introduction:

Skin cancer is currently a dangerous widespread disease there are four types of skin cancer and the first three are non- melanoma [where they do not affect the melanin pigment]. the types are (1) Basal cell carcinoma where 80% of the skin develops this cancer since it affects the lower epidermis and often occurs in the head and neck. (2) Squamous cell carcinoma around 20% of the skin develops this cancer since it affects the squamous cells in the epidermis. (3) Merkel cell cancer is a highly aggressive or fast-growing and rare skin cancer that starts in hormone-producing cells just beneath the skin and hair follicle and usually occurs in the head and neck region. (4) Melanoma is cancer occurring in the melanocytes where the epidermis and dermis meet.

The cell provides skin color it's the most aggressive type of cancer about 1% of all skin cancers. The main cause of cancer is exposure to sunlight especially when it results to sunburn and blistering where the

UV rays from the sun damage the DNA in our skin causing abnormal cell formation another other cause is frequent skin contact with chemicals like tar and coal. Where statistics say currently skin cancer incidence is 8.1-79.6 in females and 5.1-

79.1 in males (the decimal of the total Skin cancer detection using image processing 2 The skin diagnosis is done by the dermatologist who removes the cell spot called a skin biopsy and checks in the microscope if it's cancer or cancer free. As one gets to determine cancer at an early stage can be treated but at a late stage, there is no treatment. But the skin biopsy process is painful and consumes a lot of time for the results to be determined, at some rate cancer might not be determined and expensive. Hence, we design a computer- based technology for skin diagnosis that is less expensive, not painful, and quick to determine the presence of cancer or not. It can determine both Melanoma and non- melanoma skin cancer. A computer should design deep learning with advanced dermoscopic algorithms based on convolutional neural network modal where with a segmented system for the implementation classification and detection of skin cancer. Since CNN is efficient, it performs a reliable lesion classification and attempts to teach the computer to gain knowledge. For example, when it sets an input of images it makes the computer

automatically categorize the input as how it trained. The deep convolutional neural network helps classify the skin lesion (any skin area with different characteristics fromthe surrounding skin, including color, shape, size, and texture)into seven categories that help their dermoscopic images cover all lesions of skin cancer. The DNN modal requires a large amount of data to train the modal to be effective for better skin cancer identification.

2. Literature background:

Deep learning is a method that teaches a computer to process data in a way inspired by the human brain. And neural networks are a subset of machine learning and are at the heart of deep learning algorithms. This modal uses deep learning and the neural network for proper image processing. We use CNN which is a class of DNN that is given a series of images and videos where it learns the features of the system and automatically extract the feature of these inputs to complete task example image classification and image semantic segmentation. CNN is mainly used in the classification of diseases. And we propose this model for skin cancer detection because it is with ability to effectively define the skin images picture and cancer detection requires high-resolution images of the skin lesion and the CNN can automatically extract the feature from the images such as its texture, tumor size, lesion borders, and the color. The following is a review of the other research papers. Skin cancer detection using image processing 3.

1. Fu et al. (2021) developed a deep convolutional neural network for skin lesion detection and diagnosis, combining different fusion strategies of multi-scale features extracted by dense players. Their model achieved promising results on several public datasets, including ISIC 2017 and PH2.
2. Gian Francesco et al. (2018) developed an automated skin lesion classification system using a CNN model to classify images as malignant or benign. The model achieved an accuracy of 83.3% in identifying malignant melanoma.
3. Haenssle et al. (2018) developed a deep-learning algorithm that can differentiate between malignant and benign skin lesions. The algorithm achieved an accuracy of 86.5%, with no significant differences in accuracy concerning lesion type or image source.
4. Guo et al. (2020) proposed a skin lesion classification system that uses deep learning algorithms for feature extraction and classification. Their model achieved a classification accuracy of 82.71% in the ISIC 2018 Skin Lesion Analysis dataset.
5. Codella et al. (2018) developed a deep□learning system to assist dermatologists in diagnosing skin cancer. Their model achieved an 86.3% sensitivity and 71.2% in identifying malignant skin lesions.
6. Li et al. (2017) designed a cascaded CNN that can classify skin lesions as benign or malignant with high precision. By integrating deep feature extraction and ensemble learning, they obtained an average AUC of 0.94.
7. Jafari et al. (2019) developed a convolutional neural network for effective skin lesion diagnosis that had an accuracy of 92.5% in identifying a dataset from the MCLASS II challenge.
8. Han et al. (2020) proposed a skin cancer diagnosis system that incorporated a deep learning model based on a dual-branch strategy, combining texture and color features. In their proposed model, the accuracy of melanoma detection reached 91.78%.

9. Brinker et al. (2019) developed a web- based tool called the "Skin Intelligence Model" (SIM), which utilizes deep learning methods to train algorithms for skin cancer detection. The model achieved excellent, skin-deep learning approaches that have shown significant progress in recent years. They have demonstrated outstanding performance in a wide range of skin cancer detection tasks, along with providing clinicians and dermatologists a powerful tool in their work.
10. Bi et al. (2019) designed a multi-stage deep learning model for skin lesion classification that combined feature extraction from a convolutional neural network and Autoencoder. This model achieved an average accuracy of 89.4% on the ISIC 4. Rosado et al. (2020) proposed a deep-learning model for the classification of benign and malignant skin lesions with an accuracy of 95% on a dataset containing 1600 dermoscopic scans.
11. Zhu et al. (2019) presented a novel hyperbolic neural network (HNN)-based skin lesion diagnosis system. In their study, they demonstrated better performance than the classical model architectures, like convolutional neural networks, in the detection of various kinds of skin lesions, such as basal cell carcinoma, squamous cell carcinoma, and pigmented nevi, among others.
12. Esteva et al. (2017) developed a deep convolutional neural network (CNN) for skin cancer diagnosis that achieved remarkable results. Their model outperformed a group of seasoned dermatologists in the classification of skin cancer sub2 Brinker lifting skin lesions. The model achieved an accuracy of 9% and demonstrated a deep learning model called Inception-v4 to classify skin lesions. Their results showed that Inception□v4 was among the best-performing models on the Skin cancer detection using image processing 4.
13. Tschandl et al. (2018) developed a deep convolutional neural network (CNN) classifier for skin cancer that outperformed dermatologists on a 1000-image dataset. Their study showed that deep learning models can achieve high diagnostic accuracy and demonstrate improved diagnostic competency.
14. Han et al. (2018) proposed a multi-scale deep convolutional neural network for skin lesion diagnosis, achieving an 88.03% accuracy on the ISIC 2017 classification challenge dataset and showing that multi- scale fusion can help improve the system's robustness and generalizability.
15. Gessert et al. (2018) introduced a deep□learning solution for the automated classification of pigmented lesions in Dervis keratosis patients. Their results demonstrated that deep learning models achieve high

accuracy and offer a promising alternative to clinical diagnosis.

16.Menon et al. (2018) developed a deep residual neural network-based ensemble model combined with image segmentation for classifying dermoscopic images. Their study showed an AUC score of 0.98 on the ISBI 2016 skin lesion classification task.

17.Hwang et al. (2019) developed a skin lesion detection system using a multimodal deep learning model that integrates visual information and text descriptions of the lesions. Their model achieved an AUC score of 94.7% on the ISIC 2018 skin lesion classification challenge dataset.

18.Hussein et al. (2019) proposed a deep learning□based approach for diagnosing melanoma skin cancer. They used InceptionV3 architecture to train their system which achieved an AUC score of 94.7% in skin lesion detection compared to dermatologists.

19.Andre Esteval and Et al. They proposed CNN and as Dataset they used a set of 129,450 images consisting of 2,032 different diseases" The effectiveness of the author's model was tested against 21 board- certified" dermatologists.

20.Zabir Al Nazi and Tasnim Azad Abir.The Datasets used were ISIC2018 and PH2. The author used Transfer learning (DCNN used for feature extraction with SVM as its classifier) The Images were augmented and the dataset size increased. The model had a Max accuracy of 92.00% achieved on the PH2 Dataset out of the many different features, The Extractors used.

21.Noel Codella and Et al. The authors used *deep learning architecture", "sparse Coding", and "support vector machine (SVM)" and used The Dataset ISIC, which contained 2624 clinical cases Two Fold cross-validation:1) Melanoma against all non-melanoma lesions, and 2) melanoma against atypical lesions only. The model yield yields 91.2% accuracy. Skin cancer detection using image processing 5

3.Methodology

1. Data Collection: Collect a large, diverse dataset of high-quality medical images of skin lesions, including benign cases and a variety of skin cancer types. Several publicly available datasets are widely used in the literature, such as the International Skin Imaging Collaboration (ISIC) dataset, which contains more than 23,000 images from diverse ethnicities. we mostly use Medical Imaging Data: Dermatological images obtained the majority of the collected data in skin cancer detection.

These imaging methods provide visualization not visible to the naked eye, which helps doctors and researchers to identify unique features of specific skin lesions.

2. Pre-processing: Pre-process the collected images to ensure consistent sizes and color spaces. computerized diagnosis represents the mainstream of detection [1, 2, and 3]. In the design and analysis of computer□aided diagnostic systems, its necessary to pre□process the image to get more accurate detection. Methods may include scaling, cropping, color normalization, and augmentation techniques.

3. Model Design: Design a deep learning model that can effectively analyze medical images and classify skin lesions based on malignant and benign cases. We use CNN architecture to be employed for skin cancer detection should be well-designed to process the unique characteristics of dermatological images.

a. Input stage: This receptive field collects input imaging data. These input images are pre□processed using techniques, such as windowing or normalization, to make sure the data is valid.

b. Convolution stage: This stage consists primarily of several convolutional layers that filter the image with various convolutional kernels to detect various features.

c. Pooling stage: after the convolution stage, there is a pooling layer to downsample the images obtained from convolutional layers by computing the maximum or average feature map values in the subsampled regions.

d. Fully connected layer stage: This layer following the pooling stage has neurons fully connected to all neurons in the previous layer. A densely connected layer extracts and combines high-level features from the previous layers' feature maps.

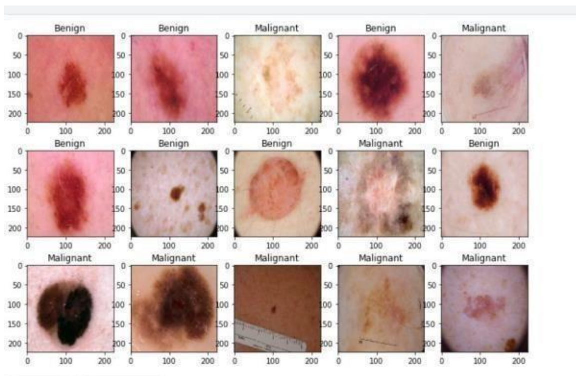
e. Output stage: Finally, the last layer outputs the predicted probability for each input image either to the malignant or benign class in binary classification. The use of SoftMax activation on the output gives the probability score to each class. Where this model requires the Rectified Linear Unit, or ReLU an activation function that helps to prevent the exponential growth in the computation required to operate the neural network. If the CNN scales in size, the computational cost of adding extra ReLU increases linearly making the model more accurate. Its function is ReLU(x)=max(0, X) The ReLu focuses on the operation of your input and basically, if your input is negative, it's going to put it to zero and then if it's positive, it's going to

Skin cancer detection using image processing 6 input that is not operated by the ReLu shows that the image does not have the specific characteristics of skin cancer and will be ignored in the process and be given as output called Benign And the inputs that are detected consist the characteristics almost or all the required characteristics to be identified hence in output will be classified as Malignant (skin cancer positive) Or as suspicious (having some characteristics but not all characteristics of skin cancer) .

4.Training: Train the model on the pre-processed dataset using supervised learning techniques. Optimizers and loss functions should be selected carefully. Can be incorporated to improve the generalizability of the trained model by using the model in different data sets to make it more accurate and identify the shortage of the model and easy rectification.

5.Validation: To Validate the trained model on a held-out subset of the dataset to avoid overfitting. Metrics, such as accuracy, the area under the receiver operating characteristic curve, and sensitivity, should be used to evaluate the model's performance. It is mainly to show the accuracy of the model.

6.Testing: The final model was tested on the data fed .



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