SKIN CANCER DETECTION AND SEVERITY PREDICTION USING DEEP LEARNING

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Abstract - *Melanoma is a malignancy that is fatal. Melanoma scenarios are more frequent in Northern India, whereas non-melanoma skin cancer cases are more common in the Northeast, especially in Nagaland, according to a new research by the Indian Council of Medical Studies (ICMR). Skin melanoma is anticipated to be the cause of over 7650 accidental deaths in 2022, according to a US Cancer Institute analysis. All around the world, the age group of 70 years and above age interval is most impacted by melanoma. The suggested approach may identify cancer types that are melanocyte, squamous cell, and basal cell. We give two approaches to a unique problem: cross-domain skin disease identification. Using two datasets pertaining to skin conditions, the network was refined.*

***Key Words*: Deep Learning, Melanoma, ImageNet, Transfer Learning, Convolutional Neural Networks.**

1.INTRODUCTION

Approximately 20 square feet make up the skin, which is the greatest component of the human body. The primary functions of skin include assisting the body in controlling body temperature, shielding interior organs from UV radiation and bacteria, and enabling touch, heat, and cold sensations. Recent years have seen a sharp rise in the prevalence of skin cancer. Most fatalities from skin cancer are caused by melanoma; the World Health Organization, for example, predicts that 232,000 cases of melanoma have been documented worldwide. Furthermore, the age difference and rate are said to be rising globally each year. With higher possibilities of long-term survival, early discovery makes treatment crucial. The survival rate drops dramatically and it gets more difficult to threaten if it is not discovered early.

The melanocyte, Squamous, and basal are the three primary groups into which skin cancer can be divided. Typically, basal cell carcinoma, the most common kind of cancer, develops very slowly and does not metastasize to other regions of the body. HPV's imperative to eradicate HPV from the body since it resurfaces often. Squamous cell carcinoma, also called squamous cell is another form of skin cancer that is more likely to progress to other areas of the body and penetrates the skin far more deeply than basal cell carcinoma. Melanocytes, the last class of cells, produce melanin in reaction to sunlight, which is responsible for the tan or brown color of skin. The melanin in these cells protects the outermost layer of skin from sunlight, but an excess of it can accumulate inside and result in malignant moles or cancer called melanoma. While basal and squamous cancers are generally considered to be benign because they tend to cause relatively little harm to the surrounding tissues, melanocyte-based malignant tumors have been deemed malignant and can be lethal.

When melanoma is discovered or diagnosed in its initial stages, it can be cured; however, if it is discovered or diagnosed in its later stages, it may spread deeper into the layer of skin and affect various regions of the body, in which case treatment may become extremely challenging. Because melanocytes are found throughout the body, melanoma is brought forth by them. A key contributing factor to the development of melanoma is skin exposure to UV light. Melanin deposits are often located in the layer of epidermis in benign lesions. The amount of melanin generated in malignant tumors is very aberrant. Until melanocytes and the melanin they produce stay in the epidermal covering, malignant lesions are not life-threatening; nevertheless, the color of the skin changes as soon as the melanocytes reach the dermal layer along with leave sediments behind. The British Skin Foundation estimates that each year, over 100,000 new instances of cancer of the skin are detected and that the illness claims the lives of about 2500 individuals. Lots of individuals worldwide struggle with skin cancer, which is becoming more common. In general, this poses issues to the global health community. Up until the age of 70, one in five Americans will have skin cancer. Each year in Europe, melanoma causes the deaths of 22,000 individuals and confirms over 100,000 new cases of the disease. However, one of the most amazing things about the cancer of the skin is that the five-year recovery probability increases to 99% when the cancer is diagnosed early, compared to a 23% likelihood when it is discovered later in the disease's course.

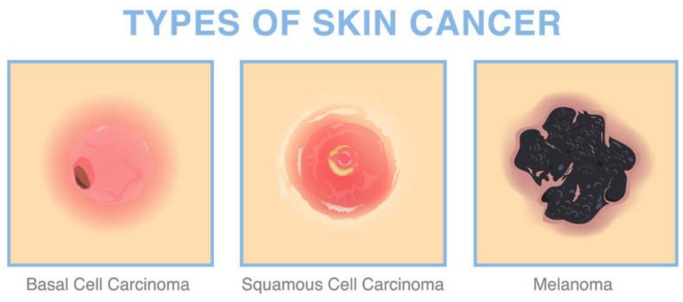


Fig-1: Types of skin cancer

As a result, it is crucial to diagnose skin cancer early. Dermatologists can identify skin cancer by a straightforward visual inspection of lesions. Even for experienced medical professionals, distinguishing between benign and malignant skin conditions can be challenging because of the subtle differences between them. As a result, it is good to have medical applications in this sector that offer robotic skin lesion assessment for decision advice. As prospective tools for the assessment of melanocytic lesions, computer-aided evaluation (CAD) systems are being explored extensively since the early 1990s. The computerized examination was initially carried out using preset methods that were well-known to dermatological experts, such as the ABCD-rule. However, these methods frequently failed both to extrapolate to new incidents or to achieve the necessary accuracy. In order to provide seasoned physicians a second opinion or to provide novice physicians with enhanced training, a number of software programs for the automatic diagnosis of melanoma in synoptic and dermoscopic pictures are now available on the market.

To improve both the rapidity and precision of diagnosis, the automatic technique can be highly beneficial. This makes it increasingly important to build algorithms for illness diagnostics that identify and use different elements from the photos. The diagnosis of illnesses is one of the numerous uses for computational imaging that has recently attracted a lot of empirical attention.

2.LITERATURE SURVEY

Research on the diagnosis of skin cancer, its severity, and different methods for classifying skin cancer disorders is offered by a number of writers and is summarized here.

[1] The primary goal of this study is to develop a system that can automatically determine if a skin cancer case is benign, a malignant tumor or neoplastic. In this study, they made use of the following methods: feature extraction, segmentation, noise reduction, picture capture, and preliminary processing. For the very initial a period of time Cubic Regression has been used in Guided Machine Learning techniques. We were able to teach the machine to identify the different stages of skin cancer and to show Benign, Melanoma, and Melanoma automatically by using this approach. Overfitting: Given that the training set is too large, the model performs well on it but cannot generalize to unfamiliar, unproved information.

[2] The goal of this study is to determine the best accurate skin cancer diagnosis and to classify melanoma as non-malignant or cancerous. A few pre-processing steps, including as the process of segmentation glare, a shadow, and removal of hair, were finished in order to accomplish this. Deep Neural Networks and Support Vector Machines will be utilized for classification. Before being utilized for classification, the classifier will be taught to understand the characteristics. The present approach is novel in that its goal is to detect abnormalities rapidly, which will help technicians improve their diagnostic skills. The International Standards Institute (International Skin Imaging Consortium) dataset is openly accessible, therefore any collection of images may be used to calculate the efficiency.

[3] The most effective techniques are used in this study to categorize all forms of cancer. The dull razor technique, the Gaussian filter, and the median filter are all employed to improve pictures and eliminate noise. Features are extracted from the segmented pictures using two methods: the GLCM methodology and the ABCD method of feature extraction procedure. Features from both strategies are combined to enhance categorization. In the end, a The Microsoft Virtual Machine classifier is used for classification in order to obtain high accuracy.

[4] This work examines how Deep Learning Studio (DLS) may be used to apply Model Driven Approach to the field of deep learning. It demonstrates DLS's capabilities and details how to generate a Deep Learning System using the tool. This work demonstrates the process of preparing dermal cell pictures for information entry and identifies cancer cells using the DLS model. The outcomes demonstrate good accuracy, with DLS models achieving an Area Underneath the Curve (AUC) of 99.77% in recognizing malignant cells from the pictures.

[5] Train and assess the system, the study made use of three databases: PAD-UFES-20, an image subset from Fitzpatrick17k, and the ISIC Dermoscopic Archive for the 2019 and 2020 melanoma detection challenges. For lesion classification, Convolutional artificial neural networks of the Inception-Re kind were employed. The suggested approach demonstrated a 94.5% accuracy rate in differentiating between benign and malignant lesions and an 89.3% accuracy rate in classifying four common skin conditions.

[6] The 11,527-image ISIC 2018 dataset was used for training and testing of the proposed technique. Prior to applying a CNN model to the test set, processes for preprocessing such data augmenting, scaling, normalizing, and picture enhancement employing ESRGAN were deployed. The system applied image advancement

algorithms on lesion pictures to boost the visibility and minimize noise. In order to minimize overfitting and enhance the overall effectiveness of the suggested deep learning approaches, a number of models, namely Resnet50, InceptionV3, along with Resnet Inception's design were trained on preprocessed lesion medical imagery.

[7] Dermoscopic skin lesion images are used by the proposed model to classify skin cancer cases. Resnet-50/CNN is used for preprocessing, classification, and training in the operational approach. To enhance image quality, the first preprocessing step is carried out using ESRGAN. Ground truth pictures are used to establish the area of interest (also known as ROI) for each segmented tumour. Then, for real-time development and skin cancer grouping, dermoscopy photos are supplied into the Resnet-50/CNN networks.

[8] In order to detect melanoma more effectively, the study presents a novel deep network architecture called Xception. Using depthwise separable convolutions and the Swish activation function, the model improves CNN's classification accuracy. Having a 95.53% F1-scoring 94.05% sensitiveness, 97.07% exactness, and an accuracy of 100%, the suggested method outperformed most advanced approaches when it came to the MNIST skin cancer dataset.

[9] An approach for segmenting non-uniform images using level-set segmentation is presented in the study. The recommended approach has a mistake percentage of 3.39%, an incidence of false positives at 3.62%, and an accurate finding rate of 94.4%. The method's ability to precisely segment lesions while being unaffected by variations in brightness, contrasts, hairs, and blood vessels is confirmed by the testing results.

[10] By adding uncertainty, fuzzy clustering lowers the number of false positives in models. Variations in image quality, such as lighting, resolution, and artifacts in dermoscopic images, can have an impact on the accuracy of the model.

[11] This paper provides a summary of the advances made in deep learning techniques for the categorisation of skin cancer. Images from various dermatological disciplines as well as frequently utilized datasets are provided. The uses of CNN-based approaches for the classification of skin cancer will be addressed in the article, including frontier problems like data disparities, cross-domain adapting, stability, and profitability. It additionally supplies relevant methods that utilize deep learning to tackle these sorts of problems.

[12] The created neural network architecture can help dermatologists with melanoma screening, according to the study's multiclass classification results. Comparisons with other approaches show how reliable and effective the method is. Real-time skin melanoma detection can be effectively addressed by the suggested approach, which can be integrated into low-resource devices and yield promising results.

[13] In the paper, a deep neural network-based smartphone app for diagnosing melanoma is presented. An average of 89% balanced accuracy and 100% recall are obtained from clinical data. Furthermore, the outcomes produced with a weighted loss function and a mutation operator inspired by DE closely match each other.

[14] AI might be a big help in the detection of skin cancer. The two primary areas of artificial intelligence (AI) utilized in the identification and categorization of cancers of the skin are shallow and deep approaches. This study shows that accuracy results are greater when fewer testing classes are included. Our data also shows that, in contrast to common assumption, greater accuracy ratings have been observed when fewer observations are included. This might be due to a number of things, such as the kind of photographs and the methods used. Further, every AI tool must first undergo autonomous outside validation on a large, varied, and unbiased database in order show its reliability and universality before it is used in a clinical environment.

[15] In this work, a Rapid Region-based neural network using convolution (FRCNN) is used to compare the precision of classification of pigmented skin lesions with the diagnosis accuracy of dermatologists. Using 5846 clinical photographs from 3551 recipients, the FRCNN achieved unpaid results: 86.2% accuracy in six-class category and 91.5% confidence in the malignant versus benign classification. A comparison review revealed that FRCNN performed better in terms of accuracy and specificity than 10 board-certified dermatologists and trainees. The method has the potential to be widely adopted by society, which might significantly enhance skin cancer prognoses and highlight the revolutionary potential of computer science in medical evaluations.

[16] The difficulty of diagnosing skin conditions—especially skin cancer—is discussed in this literature review, which also highlights the promise of big data healthcare frameworks for accurate prediction and early diagnosis in the future. The effectiveness of the fuzzy Analytical Hierarchy Process (AHP) technique in summarizing and forecasting is emphasized. The essay suggests a big data technology-based approach to classify skin cancer treatment phases. Fuzzy selection experiments using a support vector machine for classification with multiple classes and binary migration classification based on the radial basis function demonstrate the effectiveness of the approach, exceeding rivals with 90.86% effectiveness. By assisting in the classification of skin cancer severity and the identification of mass phases, the methodology illustrates the approach's possible clinical relevance.

[17] This literature review highlights the rising global incidence of skin tumors and the critical need for prompt

detection. A number of types, including deadly ones like melanoma, are caused by genetic and metabolic abnormalities. A specific type of deep learning called Convolutional neural networks, more commonly has shown potential as a skin cancer detection tool. For precise skin lesion classification, the study suggests a CNN architecture consisting of five layers that uses diagnosis labels and image pixels as inputs. To assess tumor intensity after classification, a different approach makes advantage of OpenCV color prediction. This approach has the potential to enhance early detection and ultimately save lives by leveraging the capabilities of state-of-the-art deep learning algorithms in medical picture analysis.

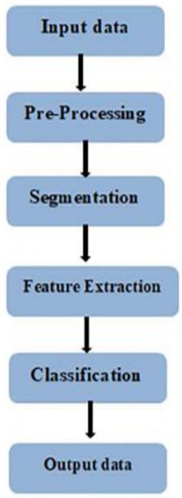
[18] This review of the literature explores the difficulties in diagnosing melanoma, highlighting the disease's rising global incidence and the vital importance of early identification. With the use of deep learning, image processing, and machine intelligence—more especially, convolutional neural networks with deep layers, or CNNs—the study explores the automated detection of carcinoma from dermoscopic skin samples. In comparison to other models, the suggested DCNN model—a hybrid of VGG 16 and LSTM—performs better. The model attains remarkable testing and training accuracies of 94.39% and 90.89%, respectively, through rigorous preprocessing and regularization techniques. This work demonstrates how state-of-the-art deep learning techniques may transform the diagnosis of melanoma and enhance the lives of patients.

[19] The worldwide impact of skin cancer is emphasized by this literature review, which also highlights how crucial early detection is to effective control. The shortcomings of the severity detection algorithms used today include large time and cost commitments as well as less-than-ideal lesion analysis. (MPNN) classifier is proposed to overcome these difficulties by using Spider Monkey Optimization for neural network training. The classifier performs better than more well-known methods like KNN, among others NB and OB RF, and SVM having a 0.10% false- positive Rates, 0.03% mistakes, and 0.98% confidence. This study demonstrates how the MPNN classifier can improve skin cancer severity detection, offering a more precise and effective diagnostic method.

[20] This literature review suggests a Graph Convolutional Network (GCN) with Delaunay triangulation for feature extraction to address the crucial problem of skin cancer misdiagnosis. Boundary extraction is aided by Delaunay triangulation, which enables the model to concentrate only on malignant lesions for more precise predictions. With benefits over conventional CNN models, GCN is particularly good at simulating interactions between image regions and structures and enables node-to-node messaging. Using few-shot and transfer learning, GCN handles a small number of annotated medical image datasets. But problems like overfitting occur, which are caused by things like unbalanced data, inaccurate feature extraction, and not enough features. The study offers insightful information about improving GCN models for more accurate skin cancer classification.

3.PROPOSED METHOD

Using deep learning and image processing, a skin disease detection and classification system can be developed in three main steps. Create a diverse dataset of annotated images of skin diseases first. Preprocess the photographs by resizing, establishing a normal and improving them to increase the dataset's variability. Lastly, use a deep learning building design, such a neural network based on convolution (CNN), to train the model utilizing the preprocessed data. As two rigorous evaluation criteria, use exactness and F1-score. Backpropagation should be used to adjust these parameters and optimize the model. Apply extraction of attributes and methods of augmentation to images to guarantee robustness.



4.IMPLEMENTATION

The recommended approach is shown, and every section is explained in greater detail below. input The proposed approach utilizes databases of high-resolution dermoscopic images. Using 800 compressed pictures from the International Standards Institute 2019 challenge dataset—which consists of eight different classes—the proposed system.

Pre-processing: Several factors need the picture acquisition process to be non-uniform. Consequently, the main goal of the pre-processing phase is to reduce or remove the backdrop or other unwanted portions of the image in order to improve the image properties, such as quality, clarity, etc. The three main preliminary processing stages are grayscale conversion, noise reduction, and picture enhancement. All the images in the proposed system are first transformed to grayscale. The Gaussian mask and a median filter are then used for noise reduction and picture enhancement. To remove undesirable hair from the area of lesion, filters are employed in addition to the Dull Razor Method. The improvement of images aims to increase an image's visibility while simultaneously enhancing its quality. The bulk of skin lesions tend to consist of skin cells and hair, which could render achieving excellent classification precision difficult. The formula for Gaussian filter is,

$$G(x,y) = \frac{1}{2\pi\sigma^2} e^{\frac{-x^2+y^2}{2\sigma^2}}$$

Consequently, the excess hair from the photographs is removed using the dull razor procedure.

Thus, reconstruction loss is defined as follows:

$$\mathcal{L}_{\text{rec}} = \alpha L_1^{\text{foreground}} + \beta L_1^{\text{background}} + \gamma L_2^{\text{composed}} + \delta \mathcal{L}_{\text{SSIM}} + \lambda \mathcal{L}_{\text{tv}}, \quad (1)$$

The Dull Razor technique is mostly used to accomplish these tasks: A) Using this grayscale morphological operation, the location of the hair on the outer layer of skin lesion is determined. b) The hair pixel is updated using bilinear interpolation once the position has been determined and the shape whether it be long or thin has been verified.

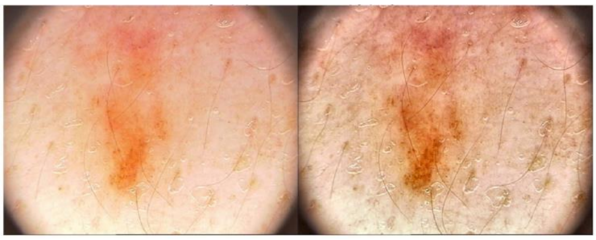


Fig-2: Image from dataset (left); enhanced image (right)

Segmentation: Divide the region that is relevant in a picture by using the segmentation method. One way to achieve this separation is to assign a similar attribute to every pixel in the image. This has the primary benefit that separated images can be processed separately from the entire image. Identifying the boundaries of the specific area is the most widely used method. Detecting similarities within a specific region is the basis for other techniques like thresholding, clustering, and region growing.

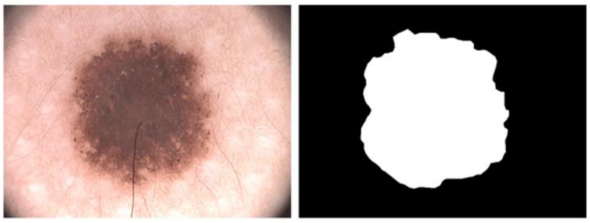


Fig-3:Segmented image

Feature extraction: In the entire classification process, feature extraction is thought to be the most important step. Feature extraction is the process of removing pertinent features from a provided input dataset so that they can be used in subsequent computations like further detection and classification.

5.CONCLUSION

Diagnosing skin cancer is a challenging assignment for dermatologists because many skin cancer colors are similar. Therefore, early detection of lesions is essential and helpful for providing patients with complete recovery from skin cancer. Deep convolutional neural networks (DCNN) models have been widely studied for the aim of identifying skin disorders. In several cases, these simulations have even yielded diagnostic results that are comparable to or superior than those obtained by dermatologists. The use of appropriate computational layers, network depth, hyperparameter tuning, and the selection of various filters and size choices are crucial aspects of DCNN design. The limited quantity and unbalanced data of publicly accessible skin lesion datasets, however, limit the use of DCNN in the detection of skin disorders. This study presents an overview and comparison of many types of CNN.

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