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ARTIFICIAL INTELLIGENCE BASED DETECTION AND CLASSIFICATION OF MELANOMA SKIN CANCER DIAGNOSTIC

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Abstract In order to analyze the input data and pinpoint three qualities, three tests—the data improvement test, the improvement ratio test, and the chi-square test—were utilized. This kind of problem with lesion diagnosis is brought on by things like hazy lesion borders, reduced color contrast, location-dependent outline variations, and complicated lesion structures. Medical personnel and researchers can save many lives by detecting the public health burden issues early and treating them appropriately to stop them from spreading to other organs of the body.A subject has a probability of developing melanoma if their skin's look changes in an odd way. Combining dermatology expertise with computer vision methods for effective melanoma detection can lead to improved solutions. Therefore, it is crucial to create alternative detection methods to help clinicians identify melanoma at an early stage.

Keywords : Artificial Intelligence, Melanoma Diagnostic, Deep Convolutional Neural Network

I. INTRODUCTION

Melanoma, a fatal variety of skin cancer, continues to be a major problem for global public health. Early detection and precise diagnosis are essential for enhancing patient outcomes due to the disease's rapid course, high fatality rates, and propensity to metastasis. Although effective, conventional diagnostic techniques frequently rely on clinical judgment and can result in arbitrary conclusions. In recent years, AI in dermatology has shown tremendous promise for revolutionizing the detection and classification of melanoma. One of the most impressive uses of AI, particularly ML and DL, has been found in medical picture processing. Using massive datasets of dermoscopic images, AI algorithms may learn to distinguish minute traits, textures, and asymmetries suggestive of melanoma. The capacity to record and analyse complex visual data has the potential to improve the precision and effectiveness of melanoma diagnosis. This study investigates how artificial intelligence can revolutionize the field of melanoma skin cancer detection and categorization. By utilizing AI, we can take advantage of its unmatched precision in medical image analysis and interpretation. We aim to put light on the major contributions that AI has made to melanoma diagnoses by analyzing existing research, approaches, and developments. The technical components of AI-based melanoma detection will be covered in this work, including dataset selection and curation, picture preprocessing methods, and the training of machine learning and deep learning models. We will also talk about the difficulties and constraints of applying AI to dermatology, such as the requirement for substantial and varied datasets, worries about model generalizability, and moral issues regarding patient data privacy. A complete overview of the state of AI-driven melanoma diagnoses is another goal of this paper. We can emphasise the potential for increasing early detection rates and lowering instances of false negatives or false positives by comparing the performance of various AI algorithms to conventional diagnostic approaches.

II. RELATED WORKS

Esteva, Kuprel, Novoa, and other authors. Nature, This innovative study demonstrated that deep neural networks can diagnose skin cancer, including melanoma, with accuracy comparable to that of dermatologists. By using a sizable dataset of dermoscopic images to train a convolutional neural network (CNN), the authors were able to obtain excellent diagnosis accuracy.H. A. Haenssle and Fink (2018) When compared to 58 dermatologists, the diagnostic efficacy of a deep learning convolutional neural network was improved for finding dermoscopic melanomas. In this study, the capacity of dermatologists and CNN to recognise melanoma from dermoscopic images was examined. The capability of AI-based tools to enhance clinical decision-making was demonstrated by the CNN, whose diagnostic accuracy was comparable to that of a panel of dermatologists.B. N. Akay, N. Codella, P. Tschandl, and others. The categorization accuracy of pigmented skin lesions was assessed in a global, open, web-based diagnostic investigation for both human readers and machine learning algorithms. The Lancet Oncology, 20(7), p. 938–947. This international study evaluated the classification of pigmented skin lesions, including melanoma, by dermatologists and machine learning techniques, including deep learning models. The results demonstrated that AI algorithms are capable of matching subject-matter experts' accuracy.2019; This study assessed the performance of deep learning models against a large number of dermatologists in order to classify dermoscopic pictures for melanoma. The deep learning models outperformed the majority of dermatologists, highlighting their potential as diagnostic tools. According to Arima, H., Mimori, T., Ishida, et al., in 2020.a thorough analysis of the use of artificial intelligence in the detection and diagnosis of skin cancer.97(1), 8-16, Journal of Dermatological Science. An overview of numerous AI-based methods for identifying and diagnosing skin cancer, including melanoma, is given in this systematic study. It covers various AI methods, dataset characteristics, and emphasises how AI may affect dermatology. BenTaieb, A., Kawahara, J., et al. Deep learning-based integrated melanoma recognition. 79, 101686 Computerized Medical Imaging and Graphics. This paper offers an integrated method for melanoma recognition that integrates various deep learning models. By combining data from other networks, the authors show increased performance, increasing the possibility of precise diagnosis.Uddin, S., Haque, S., and others (2021).Using an Ensemble of CNN for AI-Based Skin Cancer Detection. IEEE Access 9, pages 16724–16733. With an emphasis on melanoma, this research suggests an ensemble of CNNs for the identification of skin cancer. The study shows how integrating various CNN architectures can improve diagnostic precision.Celebi, M. E., N. C. Codella, et al. Using a convolutional neural network, melanocytic neoplasms, including melanoma, are categorised at the dermatologist level. 157(8), 908-914. JAMA Dermatology. The accuracy with which a CNN can categorise melanocytic neoplasms, such as melanoma, is tested in this study. The results highlight AI's potential to support clinical judgement.

III. PROPOSED SYSTEM

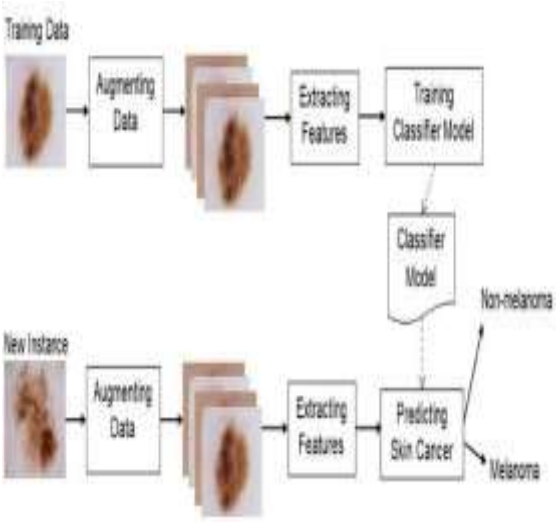

Figure 3.1 Overall Proposed System

With 100,000 new instances of melanoma and 230,000 new cases of non-melanoma cases worldwide each year, skin cancer is a significant global health concern.. Excessive UV exposure has been identified as a key risk issue for the expansion of skin cancer in recent research. The best way to reduce the number of skin cancer deaths is to promptly diagnose any skin abnormalities, as melanoma patients have a 99 percent five-year survival probability when discovered and tested at an early stage. It is necessary to establish an automated, effective approach for the diagnosis of skin cancer because dermatologists are unable to provide an accurate diagnosis of the disease. In comparison to earlier studies or experienced dermatologists, this research investigates an effective computerized technique for classifying skin cancer with improved calculation measures. We used a MobileNet model that was transfer-learned on 10015 dermoscopy images from the HAM10000 dataset after being fine-tuned on roughly 12,80,000 photos from the 2014 Image Net Challenge. For the seven classes in the dataset, the model utilized in this work has an overall accuracy of 83.1%, with top-2 and top-3 accuracy of 91.36% and 95.34%, respectively. Additionally, it was discovered that the weighted averages of precision, recall, and f1-score were 89%, 83%, and 83%, respectively. This approach might help dermatology experts make decisions when they're needed most. Deep learning is used to augment the dermatologist's aid. The core of the method is that a computer is taught to recognize the issue by examining skin cancer photographs that can quickly identify early stage.

SKIN CANCER IMAGE DATASET

Make a directory of the photos from various sources as a first step. There are 46,466 RGB images with a dimension of 224x 224 pixels in the current collection, HAM10000. The dataset is separated into 7 classes; All class has about 4,000 images, of which 75% are utilised for testing and 25% are used for validation. The test set is then used to construct a validation set.

IMAGE PRE-PROCESSING

Skin lesion image pre-processing was done using Keras Image Data Generator. The validation set was selected from the dataset photographs that did not repeat any training data in order to guarantee the validity of the validation process. Images may need to be scaled or resized to fit the specifications of an algorithm or model. This may include changing the resolution or aspect ratio. The pixel values can be normalized by scaling to a specific range, such as 0 to 1. To be accepted, the values of pixels must be transformed to have a normal of zero and a deviation from the mean of one. This can speed up and stabilize the neural network training process.

IMAGE SEGMENTATION

The technique of segmenting an image involves breaking it up into smaller pieces that are significantly/perceptually homogeneous in terms of desired qualities like color, texture, etc. In order to provide a description or classification of the image, Segmentation of an image is often used for identifying objects, determine an image's borders, weed out unwanted elements, compress and modify images, and manipulate and display data. This method is widely utilized, particularly in the processing of medical images.

MobileNet CNN Architecture

The MobileNet (CNN) used in the current work receives input photos from various levels.

Incoming layer MobileNet can use a variety of input layer sizes made up of various width factors. MobileNet accepts photos with input resolutions up to 224x224 pixels.

Zero padding layer: Most image recognition algorithms employ non-zero border conditions, while MobileNet models temporal data using symmetric padding layers, which shouldn't interfere with the temporal order. The original data of an image is maintained using the padding layer.

Conv2D layer: Although the movement of filters within a picture occurs in two dimensions, this suggests that a convolution process takes place in three dimensions. To give a Tensor Flow of results for the convolution kernel, the Conv2D layer convolves a layer. When the layer is used as the initial layer in the model, keyword variables have to be provided. For the convolutional layer, a 3x3 filter size was employed.

Batch Normalize layer: Every training mini batch of the model is normalised using this layer as a component of the architecture. It makes it possible to employ a faster learning rate. This can occasionally work as a regularizer, eliminating the dropout process.

ReLu layer: Before batch normalisation layer comes ReLu layer. The MobileNet ReLu activation layer includes a ReLu function. Quick network convergence is made possible by the non-linear ReLu function. ReLu avoids making activation challenging.The artist used a 2x2 filter on the ReLu layer.

Depth wise Cov2D: In the initial stage of the model, the depthwise conv2D function allows convolution upon each input channel individually in a depthwise spatial solution. It uses a depth filter with a size of 1x1.

In order to avoid the overfitting that occurs in completely linked layers, the global-average function gathers the average of pools from each preceding convolutional layer. By doing this, a model's size is reduced and its prediction speed is increased.

Dropout: This regularisation method is applied to deep learning. For the purpose of avoiding overfitting in large networks as well, the drop out method excludes neurons that were randomly selected during the training phase of a model.

IV RESULTS AND DISCUSSION

The four primary performance indicators for segmentation and classification deep learning models are Accuracy (Acc), Dice Coefficient (Dice), Sensitivity, and AUC. These standards were used to evaluate the several models that were looked at in this paper. They are described below:

Coefficient of Dice This gauges how closely the projected output and the actual resultresemble each other. It's described as

$$\mathrm{DSC} = \frac{2TP}{FP + 2TP + FN}$$

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Sensitivity (SEN) is the percentage of expected (predicted) favourable outcomes that actually occur.

Sensitivity

Specificity(SPE) This is the percentage of predicted (negative) results among those who actually tested negative.

$$\text{Specificity} = \frac{TN}{TN + FP}$$

Accuracy (ACC): It assesses how many of the instances that were studied actually produced true outcomes, including both true positives and true negatives.

$$\text{Accuracy} = \frac{TP + TN}{TP + TN + FP + FN}$$

Area under the curve (AUC) for receiver operating characteristic (ROC): This evaluates the performance across all potential classification criteria. AUC ranges in value from 0 to 1. The area under the ROC curve, which plots true positive rate (TPR) against false positive rate (FPR) or sensitivity versus 1-specificity, is known as the AUC.

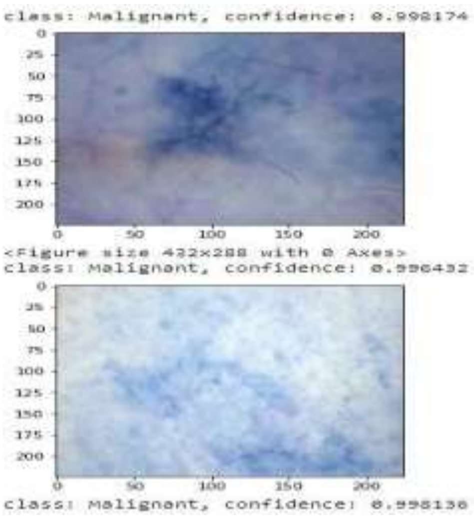

Figure 4.1 Area under the curve

Figure 4.2 Screenshot Healthy Cells Prediction

Figure 4.3 Screenshot Cancer Cells Prediction

V CONCLUSION

Since there has been an increase in the prevalence of skin cancer over the past few decades, it is vital that we advance towards an efficient and trustworthy automated approach for identifying skin cancer so that prompt and extremely accurate forecasts may be made. In this study, Applying the MobileNet model learned on a total of 10589 dermoscopy images from the HAM10000 dataset, we demonstrated the efficiency of deep learning in computerised dermoscopic multi-class skin cancer classification. On seven diagnostic tasks, we were able to equal the performance of experienced dermatologists, with a total precision of 83.1% for the dataset's seven classes and the basis-2 and the highest-3 accuracy of 91.36% and 95.34%, correspondingly. We conclude that a real-time computer-aided system for automated medical diagnosis systems can be developed using the MobileNet paradigm. In additional to having a simpler and quicker design than earlier proposed models, the MobileNet model proved accurate and reliable functionality.

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