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Skin Lesion Segmentation and Multiclass Classification using Deep Neural Networks with Transfer Learning Models

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ABSTRACT:

The skin, a vital protective barrier of the human body, plays a pivotal role in shielding from external elements. Identifying skin diseases early is crucial to prevent their progression into potentially life-threatening conditions like skin cancer. However, distinguishing these diseases at an early stage, when they bear a resemblance to one another, poses a significant challenge. Addressing this challenge necessitates the development of an innovative automated system adept at swiftly and accurately detecting various skin lesions depicted in biomedical images. In the field of healthcare, deep learning has shown promise, garnering considerable attention for its potential in managing a spectrum of disorders, including skin conditions. This work explores skin cancer classification methodologies aimed at preventing the progression of its consequences. It focuses on a process that categorizes skin cancer into seven distinct classes. The proposed approach involves two key steps: Segmentation followed by subsequent Classification. The segmentation phase leverages some models to delineate regions of interest, while the subsequent classification stage employs transfer learning models. These transfer learning models utilize the segmented mask images as input for precise classification.

Keywords: *Skin-Cancer, Segmentation, Classification, Attention U-Net, Transfer Learning, Deep Learning.*

I. INTRODUCTION

Skin cancer is a widespread and potentially life-threatening disease resulting from the transformation of skin cells, regularly actuated by delayed introduction to bright (UV) radiation from the sun or counterfeit sources such as tanning beds. The three essential sorts of skin cancer incorporate Basal Cell Carcinoma (BCC), which typically appears as small, shiny bumps or nodules with visible blood vessels; Squamous Cell Carcinoma (SCC), less prevalent but more aggressive, characterized by red, scaly patches or raised bumps; and Melanoma, the most severe variant originating in pigmentproducing cells (melanocytes), distinguished by irregular borders, uneven color, and the propensity to metastasize. The ramifications of skin cancer range from localized skin damage to the critical threat of metastasis, emphasizing the critical importance of early detection and intervention. To achieve this, medical imaging techniques play a pivotal role, where Segmentation and classification are crucial elements In the realm of medical image analysis, specifically within the domain of diagnosing skin cancer.Segmentation involves identifying and isolating tumors or affected areas within an image, while classification categorizes these regions into specific types of skin cancer, distinguishing between benign and malignant lesions. In the last few years, deep learning, a subset of machine learning, has surfaced as a potent asset in the analysis of medical images, especially in the domain of skin cancer classification. Convolutional Neural Networks (CNNs), a prominent architecture within deep learning, demonstrate proficiency in tasks associated with image recognition. The efficacy of deep learning in classifying skin cancer is attributed to its capacity to independently learn pertinent features from data, eliminating the necessity for manual feature engineering. Additionally, deep learning models are adept at recognizing complex patterns and subtle variations in images, which is important in the nuanced domain of skin cancer detection. The scalability and adaptability of deep learning models are particularly advantageous, allowing them to handle large datasets with intricate structures inherent in medical imaging. Transfer learning contributes significantly to the efficacy of deep learning models in medical image analysis, particularly in skin cancer classification part. Pre-existing models trained on extensive datasets like ImageNet can undergo fine-tuning. for these tasks, even when the medical dataset is relatively small.

This strategy capitalizes on the acquired knowledge from the comprehensive dataset to adjust the model for the distinct characteristics present in skin cancer images, enhancing its performance and generalization capabilities. The generalization capability of deep learning models to new, unseen data contributes to their robustness in real-world scenarios.

II. LITERATURE SURVEY

H. L. Gururaj, N. Manju, and A. Nagarjun, A. et al. The paper proposes a novel method named Deep Skin for skin cancer classification, with the point of upgrading early location and exact conclusion of skin cancer through the utilization of Convolutional Neural Systems (CNN) and exchange learning procedures. The dataset utilized is HAM10000, comprising 10,015 dermatoscopic pictures of skin injuries over seven unmistakable classes. Preprocessing strategies are executed to convert the crude information into a appropriate organize for analysis. Transfer learning techniques such as DenseNet169 and ResNet50 are applied to train the model on this dataset and yield results. Performance evaluation is conducted using metrics such as f1_score and accuracy.

N. Nigar, M. Umar, M. K. Shahzad, S. Islam, and D. Abalo, et.al, A novel reasonable counterfeit insights (XAI) based framework is proposed for skin injury classification, pointed at improving exactness and encouraging levelheaded determination in earlystage skin cancer. The system's approval is conducted utilizing the Universal Skin Imaging Collaboration (ISIC) 2019 dataset. . The methodology involves preprocessing dermoscopy images through resampling, cropping, and resizing. To improve accuracy and mitigate overfitting, data augmentation techniques are applied. Feature extraction is performed using the ResNet18 algorithm, while prediction explainability is achieved through the LIME framework.

Lynn, N. C., & Kyu, Z. M. et.al, The paper presents a systematic approach for segmenting and classifying melanoma skin cancer from lesion images. The proposed method encompasses several key steps, including hair and noise removal, segmentation, application of a meanshift algorithm for melanoma detection, and feature extraction. Classification tasks are performed using kNN, decision tree, and SVM classifiers. Evaluation results demonstrate the promising performance of the system in melanoma diagnosis, with accuracy tested and compared against other methods. Overall, the paper offers a comprehensive strategy for skin lesion image analysis, highlighting successful segmentation and classification techniques.

Ali, K., Shaikh, Z. A., Khan, A. A., & Laghari, A. A..et.al, The study utilizes EfficientNets, a variant of convolutional neural systems, for the classification of multiclass skin cancer. An picture preprocessing pipeline is created, taken after by exchange learning utilizing pre-trained ImageNet weights.

Finetuning is at that point conducted on the broad HAM10000 dataset, which comprises of dermatoscopic pictures. The top-performing demonstrate accomplishes surprising measurements, counting an F1 Score of 87% and a Top-1 Precision of 87.91%. Interests, middle complexity models such as B4 and B5 outperform more complex counterparts in performance. The research underscores the efficacy of AI-based methodologies, particularly leveraging EfficientNets, in achieving accurate skin cancer classification. This holds significant promise for advancing early-stage diagnosis and enhancing preventative measures against this prevalent disease.

Nawaz, M., Mehmood and Z., Nazir, T. et.al, An mechanized approach is proposed for the early discovery and division of skin melanoma, leveraging a combination of profound learning and fuzzy k-means clustering. The methodology encompasses several key steps. Initially, images in the dataset undergo preprocessing to eliminate noise, address illumination issues, and enhance visual information. Subsequently, faster regionbased convolutional neural networks (RCNN) are employed to generate fixed-length feature vectors from the preprocessed images. Following this, fuzzy k-means clustering (FKM) is applied to accurately segment the melanoma-affected areas of the skin, accommodating variations in size and boundaries. The proposed method is rigorously evaluated on standard datasets, including ISBI-2016, ISIC-2017, and PH2, showcasing superior performance compared to existing approaches. Average accuracies of 95.40%, 93.1%, and 95.6% are achieved on the respective datasets, underscoring the effectiveness and reliability of the proposed approach in skin melanoma detection and segmentation..

Ali, M. S., Miah, M. S., Haque, J., Rahman, M. M., & Islam, M. K. et.al, The paper introduces an enhanced method for skin cancer classification utilizing deep convolutional neural networks (DCNN) with transfer learning. The approach comprises several crucial steps. Initially, preprocessing techniques are applied to eliminate noise and artifacts from skin lesion images using filters or kernels. Subsequently, normalization procedures ensure consistency in color illumination by normalizing input images. Feature extraction follows, where relevant features are extracted from the normalized images to facilitate accurate classification. Additionally, data augmentation techniques are utilized to upgrade the preparing dataset. Besides, the paper incorporates a comparison of the proposed DCNN show with other prevalent exchange learning models such as AlexNet, ResNet, VGG-16, DenseNet, MobileNet, and more. The assessment of the HAM10000 dataset illustrates eminent precision rates of 93.16% for preparing and 91.93% for testing, showing the model's unwavering quality and strength in recognizing between generous and threatening skin injuries.

Wang, Z., Lyu, J., & Tang, X. et . al, This study presents autoSMIM, a method designed to tackle challenges in skin lesion segmentation by employing super pixel-based masked image modeling within a self-supervised framework. The primary aim is to accurately segment skin lesions from dermoscopic images to facilitate early diagnosis and prognosis of various skin diseases. Three skin lesion segmentation datasets, namely ISIC 2016, ISIC 2017, and ISIC 2018, are utilized. These datasets contain dermoscopic images annotated with labeled boundaries or masks for skin lesions. Evaluation metrics include Dice Similarity Coefficient (DSC), Jaccard index (JAC), and Accuracy (ACC). The future trajectory of this research involves validating the effectiveness and adaptability of autoSMIM on other medical image types and segmentation tasks, such as skin disease classification and anomaly detection.

Xie, Y., Zhang, J., Xia, Y., & Shen, C. et. al, The paper introduces MB-DCNN, a novel model that integrates deep convolutional neural networks to simultaneously perform segmentation and classification tasks. Comprising a coarse division arrange, a mask-guided classification organize, and an upgraded division organize, the show encourages common information exchange to upgrade precision. To address challenges related to lesson awkwardness and hard-easy pixel dissemination in skin injury division, the analysts propose a novel rank misfortune combined with the Dice misfortune in division systems. Assessment of the proposed demonstrate is conducted on two datasets, ISIC-2017 and PH2, illustrating predominant execution in both skin injury division and classification compared to existing strategies. The Jaccard File is utilized as the metric for skin injury division, whereas the Area under the Curve (AUC) is utilized for skin injury classification appraisal.

M. A. Rasel, U. H. Obaidellah and S. A. Kareem. et. al, The study aims to explore the efficacy of various nonlinear activation functions within a Convolutional Neural Network(CNN) for the classification of melanoma-related skin injuries. The inquire about utilizes the PH2 dataset at the side datasets from the Universal Skin Imaging Collaboration (ISIC) chronicle. Evaluation metrics include Sensitivity (SE), Specificity (SP), Precision (PR), Accuracy (AC), and F1 score. Two distinguished impediments of the proposed CNN show are the compelled estimate of the preparing datasets and the confined number of illness classes consolidated into the demonstrate. Future endeavors may center on preparing the show on bigger datasets such as HAM10000, ISIC2016, ISIC2017, ISIC2018, ISIC2019, and ISIC2020 to upgrade its viability . Additionally, the expansion of disease classes in the output layer could be pursued.

M. A. Anjum, J. Amin, M. Sharif, H. U. Khan, M. S. A. Malik and S. Kadry, et. al. The objective is to create a system capable of precisely identifying, segmenting, and categorizing skin lesions at an early stage. To assess the proposed strategy, it is assessed on the noticeable MICCAI ISIC challenging datasets crossing from 2017 to 2019. These datasets are broadly utilized in restorative picture investigation, particularly for skin injury location and classification assignments. The proposed strategy utilizes YOLOv2 with ONNX and SqueezeNet for exact injury localization. Semantic division methods are utilized to classify person pixels, whereas profound highlights are extricated utilizing ResNet-18. These optimized highlights are along these lines utilized with OSVM and O-NB classifiers for skin injury classification. The assessment measurements utilized include mean average precision (mAP) and accuracy.

III. METHODOLOGY

Identifying skin cancer in its early stages poses a significant challenge for dermatologists. Utilizing deep learning methodologies, as illustrated in Figure 1, proves instrumental in classifying images depicting the seven types of skin cancer.

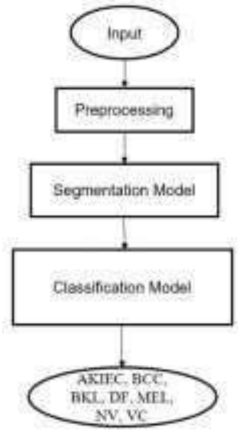

Fig 1: Flow diagram

The above figure represents the process flow of the model right from the start. Initially, the skin image undergoes preprocessing before being forwarded to the trained segmentation model for image segmentation. Subsequently, the segmented image is directed to the classification model for type classification.

DATASET DESCRIPTION:

The dataset comprises 10,015 dermatoscopic images sourced from HAM10000, a collection by the National Institutes of Standards and Technology (NIST). These pictures speak to noteworthy demonstrative categories of pigmented skin injuries, counting actinic keratoses and intraepithelial carcinoma/disease Bowen's (AKIEC), basal cell carcinoma (BCC), and kind keratosis-like injuries (such as sun based lentigines/seborrheic keratoses, lichen planus angiomas, angiokeratomas, pyogenic granulomas, and hemorrhage, vasc).

Our test points to classify these skin injuries into seven categories:AKIEC, BCC, BKL, MEL, NV, SCC, and DF. Different measurements are utilized to evaluate the segregation execution of our classification show.

Data Preprocessing:

Hair Removal-

Hair removal in skin images, a crucial preprocessing step, employs thresholding to segment hair from the background. This method relies on setting a threshold value based on color or intensity differences between hair and skin. Pixels exceeding this threshold are classified as hair, facilitating its isolation from the skin. While straightforward and computationally efficient, thresholding's effectiveness may be limited when hair color closely resembles skin. Nevertheless, it remains valuable, particularly in scenarios with distinct contrast between hair and skin. Thresholding aids in enhancing the accuracy of subsequent dermatological image analysis tasks. Its simplicity underscores its significance in optimizing image processing pipelines. However, supplementary techniques may be necessary in challenging cases. Overall, thresholding represents a fundamental yet valuable approach to hair removal for skin image analysis.

Data Augmentation-

A widely used technique for enhancing the generalization abilities of deep neural networks is data augmentation, which serves as a form of implicit regularization. This method involves applying random yet realistic transformations to augment the variety and quantity of training data, particularly in image processing and computer vision tasks. Examples of transformations include resizing, rotation, flipping, among others. By diversifying the existing data, data augmentation aids in creating a richer training set, leading to improved model training.

Various options are available for data augmentation, including top-down transformations and side-on transformations. These can be summarized as follows:

1. Basic transformations: This includes changes in angles (rotation) and side-on illumination transformations.
2. Top-down transformations: These involve combinations of angle and illumination changes, as well as rotation about the vertical axis.
3. Adjustments in lighting, angle, and rotation: This includes rotations of 90, 180, or 270 degrees around the horizontal axis.

SEGMENTATION:

The Attention U-Net represents a modified rendition of the conventional U-Net framework, extensively employed in semantic segmentation undertakings. Semantic segmentation entails the assignment of a class label to each pixel within an image, effectively partitioning the image into coherent regions. A notable enhancement offered by the Attention U-Net lies in the integration of attention mechanisms into the U-Net architecture. These mechanisms empower the network to prioritize relevant portions of the input data while disregarding extraneous or noisy information. This proves particularly advantageous in segmentation tasks, where certain areas of an image hold more significance or provide greater informative value than others.

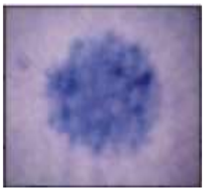

Fig 2: Image of Skin Lesion

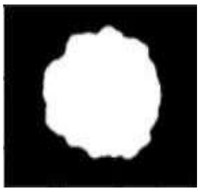

Fig 3: segmentation of skin Lesion

ResNet-50:

The demonstrate is prepared utilizing ResNet-50, a convolutional neural arrange engineering created by Microsoft Inquire about and presented in their 2015 paper "Profound Leftover Learning for Picture Acknowledgment." ResNet-50 is portion of the ResNet family, known for its inventive approach to tending to the challenges of preparing exceptionally profound neural systems. Its key include is the consolidation of remaining associations, moreover known as easy route associations. These associations relieve the vanishing angle issue, permitting for successful preparing of systems with up to 152 layers.

Residual connections enable the network to learn residual functions, simplifying the optimization process for deeper networks. ResNet-50 comprises 50 layers, including convolutional layers, pooling layers, and fully connected layers. Its modular structure consists of residual blocks, each containing multiple convolutional layers. ResNet-50 has gained widespread adoption in various computer vision tasks, particularly in image-related applications.

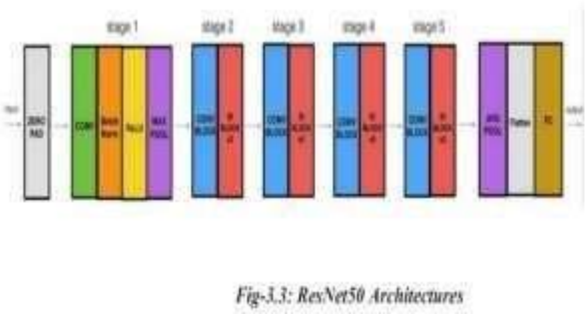

Fig 4: Resnet50 Architecture

IV. Results and Discussion

Performance Metrics:

To assess classifier performance, this section presents common quantitative metrics. In classification, outcomes are typically classified as normal or abnormal, designated as positive or negative classes, respectively. Predictions can be true or false, indicating correct or incorrect outcomes, leading to the classification's four states known as the confusion matrix:

True positive (TP) , True negative (TN), False positive (FP) False negative (FN) Using the confusion matrix, Accuracy, Precision, Recall, and F1 scores are computed.

The F1 score is the harmonic mean of precision and recall.

Results:

The segmentation model achieved an impressive Dice similarity score of 0.93, indicating high accuracy in delineating objects within the images. Subsequently, the segmented images were subjected to classification using a ResNet-50 model, which attained an outstanding accuracy of 94%. Accuracy increased to 3% when compared to the base paper. This sequential workflow demonstrates the collaborative nature of segmentation and classification tasks. Segmentation serves as an essential preprocessing stage, enhancing subsequent classification performance. The notable increase in classification accuracy underscores the segmentation model's effectiveness in extracting relevant features and reducing noise. As a result, it leads to more robust classification outcomes. These findings underscore the significance of incorporating advanced segmentation techniques, such as the proposed model, to augment the efficacy of downstream image analysis tasks, thus contributing to advancements in computer vision applications.

Model	**Accuracy**
H. L. Gururaj.et al.	91.20%
Proposed Model	94%

Table 1: Accuracy comparison Table

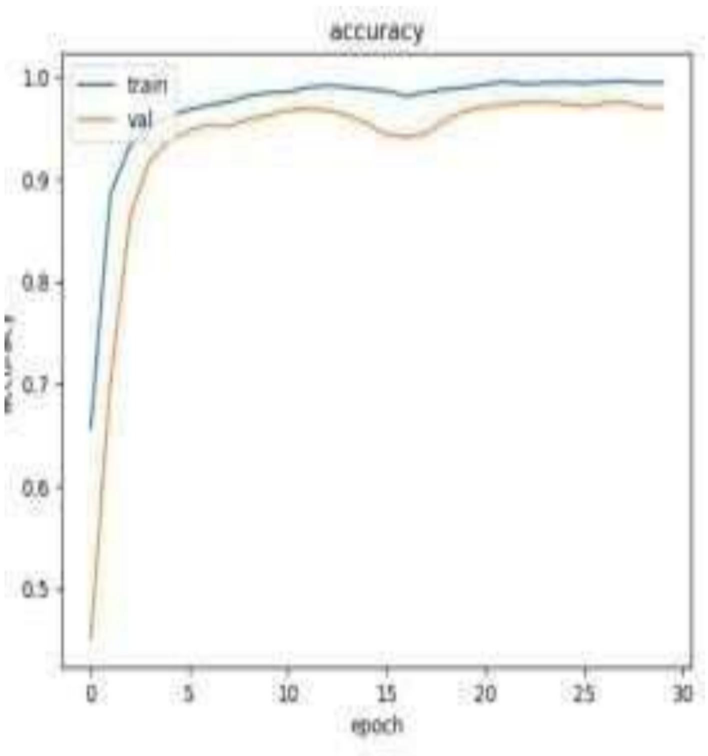

Fig 5: Accuracy-Epoch Graph

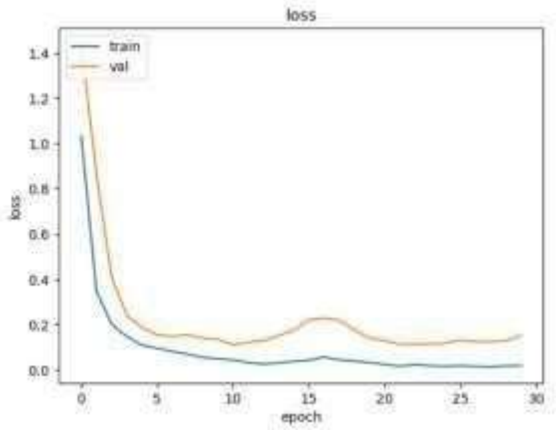

Fig 6: Loss-Epoch Graph

V. CONCLUSION

The cancer arise from the skin is rapidly becoming the most common diseases globally, largely due to exposure to sun's UV radiation. Early detection of skin cancer is crucial, given the constraints in resources available. Accurate diagnosis and effective identification are vital components of strategies aimed at preventing skin cancer. In nowadays, there has been an increase in the utilization of deep learning techniques for both supervised and unsupervised applications.

The dataset used in this study, derived from MNIST and referred to as HAM10000, comprises 10,015 samples and encompasses seven distinct forms of skin lesions. Data cleaning involved segmentation using Attention U-Net. For model training, transfer learning techniques employing ResNet-50 were employed. Future endeavors in this study aim to enhance prediction accuracy through parameter optimization.

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