Skin Cancer Detection Using Efficient Neural Network And Deep Learning

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Abstract- *Skin cancer is considered as one of the most dangerous types of cancers and there is a drastic increase in the rate of deaths due to lack of knowledge on the symptoms and their prevention. Skin cancer is a significant public health concern, with early detection being crucial for successful treatment. In recent years, machine learning techniques have shown promise in automating the classification of skin lesions, aiding in timely diagnosis and reducing the burden on healthcare systems. This paper presents an overview of the process involved in skin cancer classification using deep learning. Beginning with data collection and preprocessing, we discuss feature extraction methods, model selection, training, evaluation, and deployment strategies. Emphasis is placed on the use of convolutional neural networks (CNNs) of Efficient Net for their effectiveness in learning discriminative features from skin lesion images. Skin cancer is further divided into various types out of which the most hazardous ones are Melanoma, Basal cell carcinoma and Squamous cell carcinoma. This project is about detection and classification of various types of skin cancer using deep learning and image processing tools.*

Keywords: *convolutional neural networks, preprocessing, feature extraction.*

I. INTRODUCTION

Skin cancer malignant melanoma is the deadliest form of skin cancer Nowadays, the incidence and mortality rate of skin cancer increasing worldwide. Skin cancer, encompassing various malignancies such as melanoma, basal cell carcinoma, and squamous cell carcinoma, presents a significant health challenge globally. With its incidence on the rise, early detection and accurate diagnosis are paramount for effective treatment and improved patient outcomes. Dermoscopic imaging is the primary technique for the diagnosis of skin cancer. In recent years, the integration of machine learning techniques has offered a promising solution to automate the classification of skin lesions, thereby augmenting the diagnostic capabilities of healthcare professionals. This project delves into the application of machine learning, particularly conventional neural networks (CNNs), for the classification of skin cancer from dermatoscopic images.

Dermoscopic imaging is the primary technique for the diagnosis of skin cancer. It uses ABCD (Asymmetry, Border, Colour and Diameter) rule with many descriptors such as modification ratio, anisotropy, sharpness variation, and roundness and components average of the colour. Finally, Multiple class classifier classifies the dermoscopic images. A different features was used for SCC. Skin cancer is found to be 2 types Malignant Melanoma and Non melanoma. Malignant Melanoma is one of the deadly and dangerous type cancers, even though it’s found that only 4% of the population is affected with this, it holds for 75% of the death caused due to skincancer.

Melanoma can be cured if its identified or diagnosed in early stages and the treatment can be provided early, but if melanoma is identified in the last stages, it is possible that Melanoma can spread across deeper into skin and also can affect other parts of the body, then it becomes very difficult to treat.

Melanoma is caused due to presence of Melanocytes which are present with in the body.In this paper, a SCC system with dermoscopic images by the use of Efficient neural network and Multiple class classifier is presented.

II.LITERATURE REVIEW

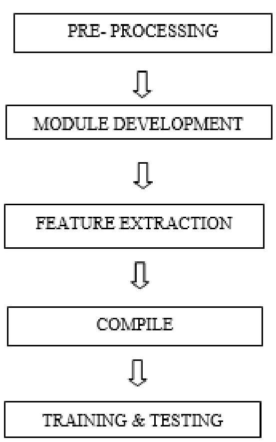
1. "Deep Learning for Skin Lesion Classification: An Overview" by Esteva et al. (2019): This paper provides a comprehensive overview of the application of deep learning in skin lesion classification, discussing various architectures and datasets used.
2. "Skin Lesion Classification Using Deep Learning Techniques" by Ha et al. (2020): Ha et al. explore different deep learning techniques for skin lesion classification, focusing on Convolutional Neural Networks (CNNs) and transfer learning approaches.
3. "A Survey on Deep Learning Techniques for Image and Video-Based Skin Cancer Detection" by Dubey et al. (2021): This survey paper summarizes recent advancements in deep learning techniques for skin cancer detection, including CNNs, Generative Adversarial Networks (GANs), and attention mechanisms.

4. "EfficientNet: Rethinking Model Scaling for Convolutional Neural Networks" by Tan et al. (2019): Tan et al. propose EfficientNet, a family of convolutional neural networks that achieve state-of-the-art accuracy with significantly fewer parameters and FLOPS (Floating Point Operations Per Second) compared to existing models.
5. "MobileNets: Efficient Convolutional Neural Networks for Mobile Vision Applications" by Howard et al. (2017): This paper introduces MobileNets, a class of efficient convolutional neural networks designed for mobile and embedded vision applications, which could be relevant for skin cancer detection on resource-constrained devices.

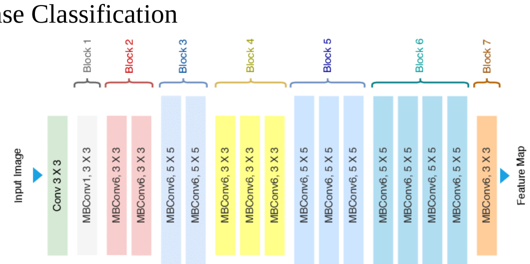
III.PROPOSED SYSTEM

A convolutional neural network (CNN) can be trained on a dataset of skin lesion images to accurately classify them as benign or malignant. Techniques like transfer learning can be employed to leverage pre-trained models for better performance, especially with limited data. Efficient architectures like MobileNet or EfficientNet can be used to ensure fast inference on mobile devices without sacrificing accuracy. Additionally, techniques such as data augmentation and ensembling can further enhance the model's performance. It's crucial to ensure the model's robustness and generalizability by validating it on diverse and representative datasets.

BLOCK DIAGRAM



Skin Disease Classification



Architecture: Efficient net

IV. IMAGE PRE-PROCESSING

Detecting skin cancer using deep learning involves training a neural network to analyze images of skin lesions and classify them as either benign or malignant. Preprocessing plays a crucial role in enhancing the quality of input data for the neural network, thereby improving its performance.

4.1.RE SIZE

- Image preprocessing involves a variety of techniques used to prepare images for analysis or further processing. Resizing is one of the common preprocessing steps, especially when dealing with images of different dimensions. Resizing an image involves changing its dimensions, either reducing or enlarging it.
- Resize all input images to a standard size, typically square dimensions like 224x224 pixels or 299x299 pixels,
- Color Space: Convert images to a consistent color space, such as RGB (Red, Green, Blue).

4.2 NORMALIZATION

Normalization is a crucial preprocessing step in skin cancer detection using deep learning. It involves transforming the input data so that it has a standard scale and distribution. Normalization can help improve the performance and convergence of Efficient neural networks.

V.MODULE DEVELOPMENT

"Module development" typically refers to the creation and refinement of specific components or sub-modules within the overall skin cancer detection system. These modules are designed to address specific tasks or challenges within the detection process.

5.1FEATURE EXTRACTION

- In this process, the deep learning model is trained on a dataset of labeled skin lesion images, where the model learns to extract features that are indicative of different types of skin cancer. These features could include texture, color, shape, and other visual characteristics.

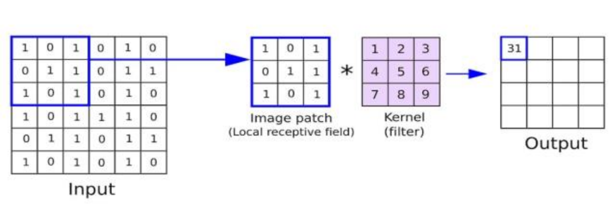
- By training a deep learning model with an efficient neural network architecture on a large dataset of skin lesion images, the model can learn to accurately classify new images as either benign or malignant, thereby aiding in the early detection and diagnosis of skin cancer.

5.1.1FILTER PRODUCT

- A3x3 filter is applied to overlapping patches of the input image. At each position, the filter computes a weighted sum of the pixel values in the patch, which produces a single output value. This operation is repeated across the entire image, generating a new "filtered" image.
- The filter products refer to the intermediate results obtained by multiplying the corresponding elements of the filter matrix and the patch of the input image being processed. These products are summed up to produce the output value at each position.

5.1.2FILTER KERNAL SIZE

- The size of the filter kernel in feature extraction refers to the dimensions of the matrix used for convolution. It determines the area of the input image or signal that the filter examines at each step of the convolution process.
- The size of the kernel is typically specified as a square matrix with dimensions such as 3x3, 5x5, 7x7, etc. Larger kernel sizes allow for capturing more complex features but may also increase computational complexity. Smaller kernel sizes are computationally more efficient but may capture fewer details.Hence common choice is to keep the kernel size at 3x3 or 5x5.



Convolution mechanism.

5.1.3 SIGMOID ACTIVATION FUNCTION

The sigmoid activation function is commonly used in binary classification tasks to predict the probability that an image contains a malignant (cancerous) skin lesion. The sigmoid function squashes the output of the model to a range between 0 and 1, representing the probability of the lesion being malignant.

Mathematically, the sigmoid function is defined as:σ(x) = 1 / (1 + e^(-x))

Where:

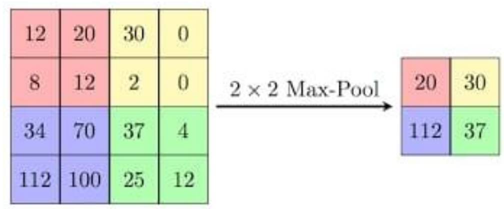
- σ(x) is the output value between 0 and 1.
- x is the input value (often the output of the neural network before applying the activation function).
- e is the base of the natural logarithm.

- After applying the sigmoid activation function, a threshold value (commonly 0.5) is used to determine the final classification decision. If the sigmoid output is greater than the threshold, the lesion is classified as malignant; otherwise, it is classified as benign.
- The sigmoid function has an "S"-shaped curve that asymptotes to 0 for large negative numbers and 1 for large positive numbers

MAX POOLING LAYER

A max pooling layer is commonly used to down sample the feature maps generated by the convolutional layers. This helps in reducing the spatial dimensions while retaining the most important features.

Max pooling takes the maximum value within a specified window (typically 2x2) and discards the rest, effectively preserving the strongest activations. This process helps in reducing computational complexity and controlling overfitting while maintaining the important features for classification.



Max pooling with 2x2 filter and stride = 2[8]

5.2COMPILE

Compile the extracted features along with their corresponding labels into a structured dataset. This dataset will be used to train a multiple class classifier.

5.2.1SPARSE CATEGORICAL CROSS ENTROP LOSS FUNCTION

Sparse categorical crossentropy is commonly used as a loss function in skin cancer detection tasks involving classification into multiple categories. It's effective for multi-class classification problems where each sample belongs to only one class, which is often the case in skin cancer detection where each image is classified into one of severalcategories like benign, malignant, etc. This loss function penalizes the model based on the difference between the predicted probabilities and the actual class labels.

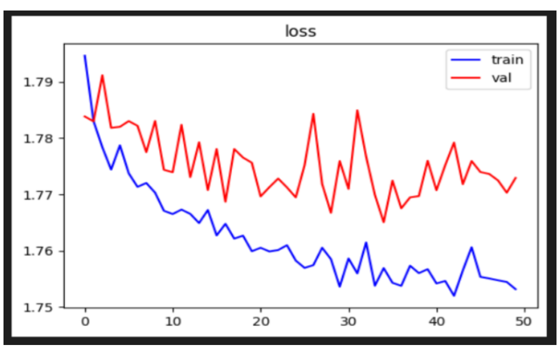
5.2.2ROOT MEAN SQUARE OPTIMIZATION

- Root mean square (RMS) optimization is a technique commonly used in various fields, including signal processing, statistics, and deep learning.
- It involves minimizing the root mean square error (RMSE) or root mean square deviation (RMSD) between observed and predicted values by adjusting model parameters.
- In deep learning, RMS optimization is often used as an optimization algorithm, particularly in training neural networks. One popular variant is RMSprop, which adaptively adjusts the learning rates for each parameter based on the average of recent gradients. This helps in efficiently navigating the parameter space during training, especially in the presence of sparse gradients or noisy data.

VI.TRAINING & TESTING

6.1 MODEL ACCURACY

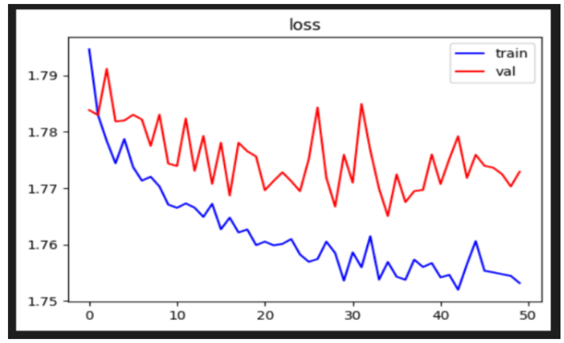
- The accuracy of models in skin cancer detection varies depending on factors such as the dataset used for training, the specific algorithms employed, and the evaluation metrics used. However, deep learning models have shown promising results, often achieving accuracies comparable to or even exceeding those of dermatologists in certain studies.
- It's important to note that while high accuracy is desirable, other factors like interpretability, generalizability, and robustness are also crucial for real-world application of these models.



6.2MODEL LOSS

Model loss refers to the measure of how well the model's predictions match the true labels during training. Lower loss values indicate better alignment betweenpredicted and actual values. Typically, models are trained to minimize loss using techniques like gradient descent.

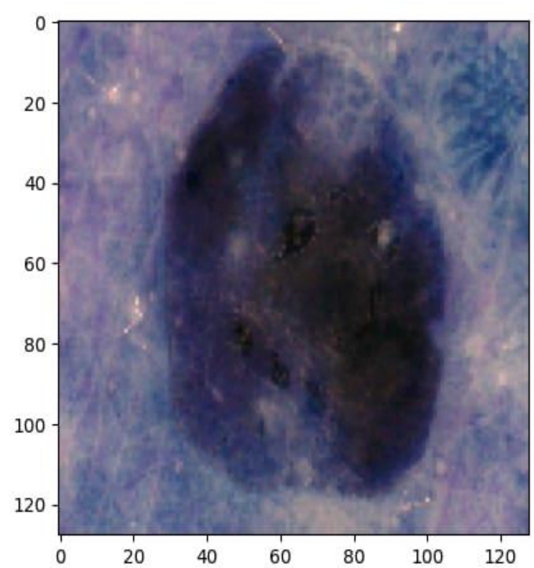
However, the specific loss function used can vary based on the architecture and goals of the model. For skin cancer detection, common loss functions include binary cross-entropy for binary classification tasks and categorical cross-entropy for multi-class classification tasks.



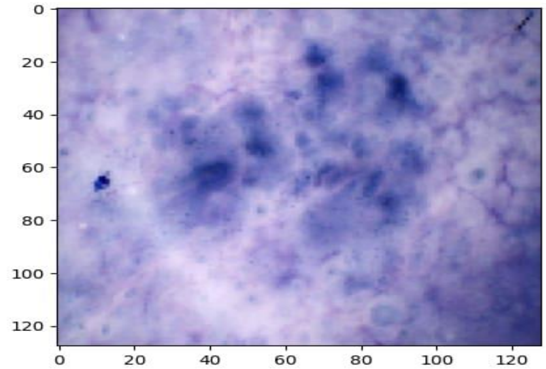
VII.RESULT

Research and applications in skin cancer detection using deep learning and efficient neural networks have shown promising results. These techniques leverage convolutional neural networks (CNNs) to analyze images of skin lesions and classify them as either benign or malignant with high accuracy. By training these models on large datasets of annotated skin images, they can learn to identify patterns indicative of various types of skin cancer.

This approach holds great potential for improving early detection and diagnosis, ultimately leading to better patient outcomes. Usingdeep learning, particularly Efficient Neural Networks, for skin cancer detection have shown promising results. These methods often involve training models on large datasets of skin lesion images, allowing the algorithms to learn to distinguish between benign and malignant lesions with high accuracy 0.96. While specific results can vary depending on the dataset used, the architecture of the neural network, and other factors, the overall trend suggests that deep learning approaches are effective in aiding dermatologists in diagnosing skin cancer.



Class: Benign



Class: Malignant

VIII.CONCLUSION

Using EfficientNet for skin cancer detection in deep learning has shown promising results. Its efficient architecture, which balances model size and accuracy, allows for effective utilization of computational resources while achieving high performance in classification tasks. EfficientNet has demonstrated competitive performance compared to other architectures like ResNet and Inception, while requiring fewer parameters and computational resources.

This makes it particularly suitable for deployment on resource-constrained devices or in scenarios where computational efficiency is crucial. Moreover, leveraging transfer learning with pre-trained EfficientNet models on large datasets like Image Net can further improve skin cancer detection accuracy, especially when training data is limited. In conclusion, EfficientNet presents a compelling option for skin cancer detection in deep learning due to its efficiency, effectiveness, and potential for transfer learning. However, continued research and validation are necessary to fully assess its capabilities and limitations in this specific application domain.

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