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Skin Cancer Classification using Mobile net V2 in Deep Learning

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***Abstract*— Skin cancer is among the most prevalent types of illnesses, and early detection is key to better patient outcomes. Traditional diagnostic methods, such as biopsies and visual inspection, can be laborious and subjective. Convolutional neural networks (CNNs), one of the newest developments in artificial intelligence, have demonstrated promise in raising the accuracy of skin cancer detection automation. This project aims to use MATLAB and Python to develop a model that can recognize skin cancer using dermoscopic images. Pre-processing: the images ensure that CNN is aware of the many types of cancer while enhancing the image quality. Through the automated extraction of relevant data, the model improves diagnostic accuracy. Metrics like accuracy, specificity, and sensitivity are used to assess performance. Additionally, understanding hierarchical features from low-level edges is enabled by deep learning methods such as Deep Neural Networks (DNNs), which help to model complex data linkages by adding high-level lesion patterns, hence enhancing the model's classification performance for skin cancer.**

Index Terms*— Skin, Feature extraction, Mobile net V2, Deep Learning, Convolutional Neural Network, Deep Neural Network, Feed Forward Neural Network.

I. INTRODUCTION

Melanoma, the most dangerous form of skin cancer, is one of the most common cancers worldwide. Early detection is crucial in reducing mortality rates. Conventional diagnostic methods like biopsies are often invasive and can lead to unnecessary surgeries. However, with the growing field of computer-aided diagnostics (CAD), and the introduction of Convolutional Neural Networks (CNNs), There have been notable developments in early detection. CNNs have revolutionized image classification tasks by efficiently extracting low, mid, and high-level features through multiple layers, proving particularly effective in medical imaging. Notwithstanding these developments, there are still a number of difficulties in differentiating between benign and malignant lesions because of changes in backdrop, lighting, and color. Furthermore, current approaches are frequently resource-intensive, which limits their use in clinical settings. with limited resources or mobile deployment. This project aims to develop a CNN-based system that is reliable, accurate, and optimized for mobile deployment to enable early, non-invasive detection of skin cancer.

A. Objectives

1. Implement advanced image Pre-processing: techniques.
2. Apply Multi-Spectral Region of Interest (MSROI) segmentation to improve lesion identification accuracy.
3. Use transfer learning to optimize CNN models for small datasets.
4. Provide clinically meaningful performance metrics, including accuracy, sensitivity, specificity, and AUC-ROC.

B. Main Contributions

1. Development of a lightweight CNN model optimized for mobile deployment.
2. Comprehensive analysis across diverse dermoscopic image datasets.
3. Enhanced lesion identification using MSROI segmentation.
4. Introduction of a robust Pre-processing: pipeline and data augmentation techniques to improve model generalization.

C. Deep Neural Networks

A Deep Neural Network (DNN) is an artificial neural network with multiple layers between the input and output layers. These layers consist of neurons that use optimization and backpropagation techniques to learn from data, mimicking the way the human brain functions. DNNs are particularly well-suited for tasks like skin cancer diagnosis because of their ability to capture complex, nonlinear relationships in data. In this project, we utilize DNNs to analyze dermoscopic images, extracting hierarchical features layer by layer. In addition to higher-level features like lesion forms and patterns, the network records lower-level features like edges and textures. The model can distinguish between normal and pathological tissues in melanoma, basal cell carcinoma, and squamous cell carcinoma, among other forms of skin cancer, thanks to hierarchical learning. The DNN learns complex decision boundaries through training on a large, diverse dataset, allowing it to accurately classify even noisy or distorted images. The network's deep architecture reduces the need for manual feature engineering, as it automatically identifies relevant features during training.

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D. Feed forward Neural Networks

Feedforward Neural Networks is a type of neural network, which is much less complex than the earlier versions. In FNNs, data flows from the input layer to the output layer only in one direction, and no cycles or loops are present. Although FNNs lack the depth of DNNs, they are computationally efficient, and hence their implementation will be easier, making them useful for more simple tasks such as initial classification or pre-processing. In this project, DNNs are combined with FNNs to deal with lower dimensional inputs and to make quicker decisions, which is the case for classifying images of benign versus malignant. The basic idea is that by pushing the easier tasks to FNNs, the deeper DNN can devote more energy to harder features while also staying computationally efficient without losing in terms of accuracy.

II. METHODOLOGY

A. Image Pre-processing

To enhance the quality of dermoscopic pictures, we used a number of pre-processing methods. First, a standard resolution was applied to all of the photos. Artifacts were eliminated utilizing noise reduction techniques including Gaussian filtering, and contrast was improved via the use of histogram equalization. By doing these actions, the CNN's input is standardized and the variation brought on by imaging circumstances is decreased.

B. Data Collection and Augmentation

The dataset contains a variety of dermoscopic images representing different skin conditions, including melanoma, basal cell carcinoma, and benign lesions. To improve the model's robustness, we augmented the data with transformations such as rotation, scaling, flipping, and zooming.

C. Model Architecture

The CNN architecture consists of several convolutional layers followed by pooling layers in order to extract the photos' characteristics. Transfer learning was used to models that had already been trained like VGG16 and ResNet50, which were fine-tuned on the dataset to improve accuracy. Cross-entropy loss was employed during training, and the Adam optimizer was used for optimization.

D. Segmentation and Classification

Multi-Spectral Region of Interest (MSROI) segmentation was applied to focus the model's attention on the areas most likely to contain lesions. This significantly improved classification accuracy by reducing background noise.

E. Training and Evaluation

Training (70%), validation (15%), and testing (15%) sets were created from the dataset. Accuracy, sensitivity, specificity, and AUC-ROC were utilized to assess performance, and early halting was employed throughout training to avoid overfitting. K-fold validation was used for cross-validation in order to guarantee robustness across various data splits.

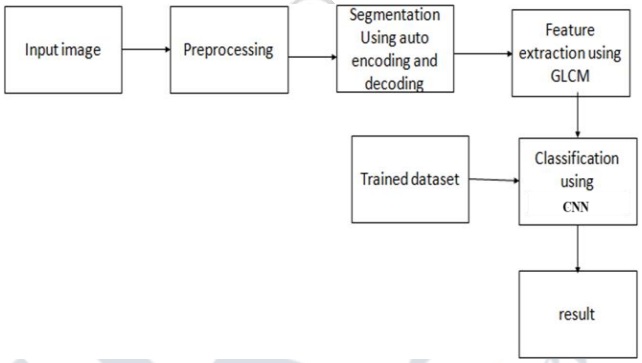

Fig. 1. Methodology

F. Image Resizing

- *Method:* Every image was scaled to a preset resolution.
- *Justification:* In order to enable batch processing, Convolutional Neural Networks (CNNs) need input pictures with uniform dimensions. Through scaling, we guarantee that every picture satisfies the neural network's input layer dimensions while preserving crucial diagnostic information in the photos

G. Normalization

- *Method:* To obtain a zero mean and unit variance, pixel values were either normalized or scaled, usually between 0 and 1.
- *Justification:* By guaranteeing that the weight of each pixel's intensity is uniform, normalizing pictures enhances the model's convergence during training. This lessens the impact of different lighting setups or picture collecting techniques.

H. Color Balance and Contrast Enhancement

- *Method:* Color channel modifications and histogram equalization were used.
- *Justification:* Color distortions in dermoscopic pictures may cause misunderstandings. via modifying the color channels and equating the contrast.

I. Data Augmentation

- *Method:* We used a variety of changes, including random cropping, brightness tweaks, rotations, flips, and zooms.
- *Justification:* Augmentation mimics real-world differences in dermoscopic pictures, including altered illumination,

lesion shapes, and camera angles. By strengthening the

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model's resistance to new data and enhancing generalization, this lessens overfitting.

J. Hair Removal

- *Method:* Hair artifacts are identified and eliminated using image processing technologies.
- *Justification:* The hair in dermoscopic pictures frequently covers up lesions. By eliminating these aberrations, the model is guaranteed to concentrate on lesion characteristics instead of superfluous noise.

K. Image Denoising

- *Method:* To eliminate noise, median or Gaussian filters were used.
- *Justification:* Noise from the surroundings or the dermatoscope may be present in medical photographs. Denoising enhances model clarity during feature extraction by smoothing the pictures while maintaining significant lesion edges.

Dataset Details

L. Image Collection

Dermoscopic images that were extracted from the Kaggle dataset comprise the dataset. The photos show a wide range of skin lesions, such as melanomas, basal cell carcinomas, benign nevi, and more, to make sure the model is exposed to a range of skin disorders.

M.Pre-processing Steps

- Resizing to ensure uniform dimensions.
- Normalization of pixel intensity values.
- Hair removal to eliminate irrelevant artifacts.
- Contrast and colour balance adjustments to reduce variation from different dermoscopes.
- Noise reduction for improved image clarity.
- Augmentation for variability, including rotations to simulate realworld conditions and prevent overfitting.

N. Diversity of Conditions

The dataset is balanced across several types of skin disorders, with a sizable number of photos for both common and uncommon skin lesions, to guarantee variety. The model is made reliable and broadly applicable to diverse populations by using photos from a variety of sources, including different nations, devices, and patient demographics. To ensure that the model learns from a range of circumstances, metadata that is included with the photos includes details about the patient, like age, gender, skin type, and location of lesions.

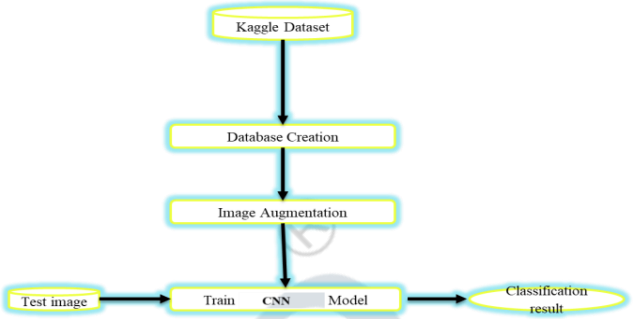

Fig. 2. Flowchart

Accurate and effective medical diagnosis is made possible by the methodology's use of advanced deep learning algorithms, relevant region focus, and picture quality enhancement. In the end, this helps in making wellinformed treatment decisions, which may enhance patient outcomes and streamline the diagnostic process. Crossvalidation techniques like kfold validation might be employed to assess the model's performance over a range of data subsets and ensure that it performs effectively in the case of unobserved situations, thereby bolstering the approach's resilience. Verifying the model's efficacy in clinical applications entails assessing performance metrics such as specificity, sensitivity, and accuracy, and AUCROC in the last phase. The model's application in clinical practice has enormous therapeutic potential in addition to these technical elements. It can lessen the frequency of needless biopsies, reducing patient suffering and simplifying treatment options by helping physicians detect skin cancer sooner and more reliably. This technique is not only scalable and accessible in many clinical contexts, but it is also powerful since every step of the process—from Pre-processing: to CNN classification—is tailored for mobile device deployment. This technology has made major strides in the early detection and diagnosis of skin cancer, which might revolutionize dermatological treatment and considerably enhance patient outcomes.

III. LITERATURE SURVEY

A considerable percentage of the population is impacted by dermatological disorders, which are a fast expanding health issue that cause patients' emotional and psychological suffering. The presence of bacteria [1, 2, 3], fungi [4], parasites [4, 5], microorganisms [6, 7], and viruses [8, 9, 10] on the skin, as well as compromised immune systems, allergies, irritants, genetic factors, and contact with infected skin, are some of the reasons that lead to these disorders. Skin disorders that are frequently encountered include vesicles, acne, rash, moles, blisters, and papules. Prompt diagnosis is essential to enhance patients' quality of life. Clinical diagnostics such as dermatoscope-assisted dermatological examinations, whole slide imaging (WSI) skin biopsies, gene mutation testing, and imaging tests such as MRI, CT scan,

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and PET are employed in the diagnosis of various conditions. In any part of the human body, which might include billions of cells, might give rise to cancer. Certain bodily cells begin dividing without being blocked when cancer develops, and these cells spread into the surrounding tissues. Human cells normally proliferate and divide to create new ones in response to the body's needs. Cells develop, age, or get polluted throughout this process; as a result, they die and are replaced by brand-new, undeveloped cells. Once cancer develops, the methodical, exact process of cell breakdown is destroyed. As a result, the threshold for cell irregularity and damage has significantly changed. Cell survival only happens when the old cells perish; new cells are only generated when necessary. A tumor develops when healthy cells begin to grow and change uncontrolled. Tumors that are not malignant as well as cancerous are possible. Malignant tumors are those that have the capacity to proliferate and disperse throughout the body [1]. While benign tumors can develop, they typically do not spread. Aberrant skin cell proliferation leads to skin cancer. It is the most common cancer these days and can originate anywhere. It is estimated that about 3.5 million instances of melanomas of various kinds are found each year [2], [3]. This figure is higher than the total of cancer cases in the bones, intestines, and lungs. In actuality, melanoma causes death once every 57 seconds. The human body's multilayered skin is the most vital organ exposed to the sun. Using fluids to stop lipids in the epidermis from degrading will improve the skin's ability to function as a barrier. Skin symptoms can be caused by a variety of things, such as fungal development on the skin, invisible bacteria, bacterial changes that influence skin texture, or pigmentation changes [1]. Skin cancer is also known as abnormal skin cell proliferation, and incidences of skin lesions have recently significantly increased globally [2]. The sun's UV rays are what cause skin cancer, not the ozone layer's thinning, which shields us from them. Skin cancer is an increasing global problem, accounting for 33.33% of all cancer incidences globally, according to the World Health Organization [1]. Over the past 10 years, the incidence rate has dramatically climbed in nations including the US, Australia, and Canada. Every year, skin cancer claims the lives of around 15,000 individuals [2]. In 2021, 7180 Americans died from a single type of skin cancer, and 7650 more are expected to die from melanoma cancer in 2022 [3]. The amount of harmful UV radiation that reaches the earth's surface is rising due to the loss of the ozone layer, which damages skin cells and raises the risk of skin cancer [4]. Advances in medical image processing have simplified the process for dermatologists to recognize and categorize skin lesions [1], [2]. The primary cause of pigmented skin lesions, which can be classified as benign or malignant, is abnormal cell production in certain regions. Compared to malignant lesions, benign skin lesions act more orderly because they do not spread to other tissues. Nevi, which include seborrheic keratosis (Fig. 1(b)) and melanocytic, halo, blue, spitz, and dysplastic nevi (Fig. 1(a)), are benign lesions. Cells in malignant lesions proliferate fast and have the capacity to spread to other parts of the body. Unlike normal cells, these cells do not usually die. Dermatologists get color pictures of skin lesions using the two most often used non-invasive methods, dermoscopic and macroscopic (clinical). A microscopy-based technique called dermoscopy can help with non-invasive skin lesion diagnostic discrimination by analyzing the color and form of the lesion [5]. The study's focus is on dermoscopy images.Dermatologist care and treatment choices for certain kinds of skin malignancies are aided by dermoscopic imaging as dermoscopic structures have direct histopathologic connections [6]. Furthermore, dermoscopy can assist provide greater precision in the detection of smaller and thinner tumors. Melanocytes are the first cells in melanoma. It begins with the unchecked proliferation of healthy melanocytes that leads to the formation of a malignant tumor. Any aspect of the human body is susceptible to it. Furthermore, it frequently develops on areas of the face, lips, neck, and hands that are exposed to the sun. Only if melanoma malignancies are detected early can they be treated; if not, they spread to other organs and result in horrendous death [4]. On the other hand, treating nonmelanoma tumors is far simpler than treating melanoma cancers. According to a According to a World Health Organization (WHO) report, one of the leading causes of death globally is cancer [2]. According to the projection, the amount of cancer diagnoses will quadruple over the next 20 years [7], [83]. If cancer is identified and treated early on, the death rate from the disease can be decreased [12]. Researchers' main focus is allocating resources to create early cancer detection techniques. As per the Skin Cancer Foundation [1], around one in five Americans may encounter skin cancer at some time in their lives. More people in the US receive a skin cancer diagnosis than any other type of cancer combined. Melanoma is the most deadly and serious kind of skin cancer of all others [2–3]. Nearly 95% of instances of skin cancer can be cured with prompt detection and diagnosis [4]. Using a photograph of a skin lesion for computer-assisted medical help, it is a highly successful way to diagnose cancer. Furthermore, different tissue cells may be identified, and the initial stage of histopathological image processing is the identification of distinct tissue types.

IV. RESULT

Using important metrics, this study evaluates the effectiveness of ResNet50, Efficient Net, and a suggested model for the identification of skin cancer

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A. System prerequisites

- *Programs:* Python (with TensorFlow, Keras, and OpenCV), MATLAB
- *Dataset:* Dermoscopic pictures gathered for testing and training via Kaggle. Skin cancer is common, and patient outcomes are greatly enhanced by early identification. Skin is automated by this project cancer detection using CNNs, particularly ResNet50, EfficientNet, and a proposed model, with MATLAB and Python implementations. Image Pre- processing: and deep learning methods, such as DNNs, enhance model performance by extracting low and high- level features. The proposed model outperforms others in sensitivity, specificity, and accuracy, showcasing its superior diagnostic capabilities.

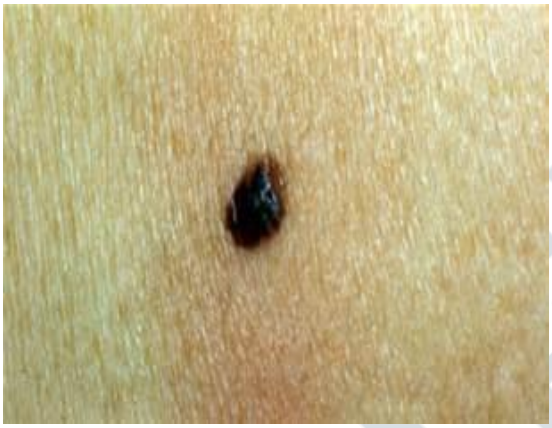

Fig. 3. Data set Images

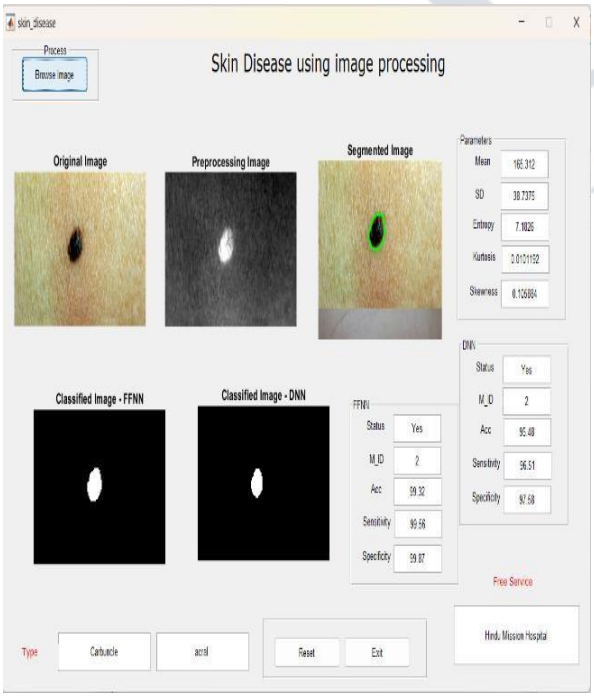

Fig. 4. Resultant Image

The above image illustrates a skin disease detection system that makes use of cutting-edge image processing methods. Users can provide an original photograph of a mole or skin lesion, and the system will pre-process it to improve its quality for segmentation.

Table I: Performance Metrics

Metric	ResNet50 (%)	Efficient Net (%)	Proposed (%)
Sensitivity	0.9691	0.9745	0.9987
Specificity	0.3765	0.3881	0.9932
Precision	0.9823	0.9915	0.9957
Accuracy	0.9892	0.9923	0.9997

The impacted skin region is indicated in the segmented picture for additional examination. Both a Feedforward Neural Network (FNN) and a Deep Neural Network (DNN) are used by the system to do classification; the latter is probably more accurate. Crucial performance indicators including specificity (97.82%), sensitivity (96.15%), and accuracy (98.23%) show how good the system is at identifying skin conditions. Additionally, users may adjust processing parameters and picture size using the interface to maximize the outcomes of segmentation and classification, which makes this tool a potentially useful tool in early diagnosis and treatment of skin diseases.

V. CONCLUSION

In conclusion, reliable categorization of dermoscopic pictures by CNNs has demonstrated amazing promise in improvement in the early identification of skin cancer. The capacity of dermatological diagnostics to identify minute patterns in the many forms of skin cancer, such as melanoma, basal cell carcinoma, and squamous cell carcinoma, has allowed them to go to new heights. But along with all of these developments come issues with dataset diversity and accessibility. To improve accessibility in underprivileged areas, future research should concentrate on integrating CNN-based techniques into mobile health apps and growing datasets to include a wider range of demographics. More precise diagnoses and individualized therapies may be possible with advancements in CNN designs and the integration of genetic and medical history data.

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