Identification and categorization of skin cancer using a Convolutional Neural Network

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Abstract:
Skin cancer is a prevalent form of cancer that poses significant health risks. It is crucial to detect this disease early, as with other cancers, to effectively manage treatment. Traditional methods of skin cancer diagnosis, however, tend to be inaccurate and can lead to unnecessary biopsies. Moreover, some existing machine learning models for cancer detection support only a limited number of skin cancer types, which can restrict their usefulness. This study developed a system using a Convolutional Neural Network capable of autonomously distinguishing between skin cancer and benign tumor lesions. The introduced model features three hidden layers with output channels scaling from 16, to 32, to 64. It employs several optimizers—SGD, RMSprop, Adam, and Nadam—with a learning rate of 0.001. Among these, the Adam optimizer yielded the highest accuracy at 93% for classifying skin lesions into benign or malignant categories using the ISIC dataset. These results outperform the current methods of skin cancer classification.

Keywords: Skin Cancer , ISIC , Convolutional Neural Network, Adam, and Nadam.

Published in IJIRMPS (E-ISSN: 2349-7300), Volume 12, Issue 3, May-June 2024

I. INTRODUCTION

Over the past decade, skin cancer has emerged as one of the fastest-growing types of cancer. Given that the skin is the body's largest organ, it is understandably the most commonly affected by cancer. [1] There are primarily two categories of skin cancer: melanoma and nonmelanoma. Melanoma is an extremely dangerous, rare, and often lethal form of skin cancer. [2] Despite accounting for only 1% of skin cancer cases, melanoma has a significantly higher mortality rate, according to the American Cancer Society. [3] Melanoma primarily affects melanocytes, the cells responsible for pigment, and begins as an abnormal growth of these normally functioning cells. [4] It can develop anywhere on the body, but areas like the hands, face, neck, and lips are more commonly affected due to constant exposure to sunlight. [5] If not detected early, melanoma can metastasize and lead to death. Types of melanoma include nodular melanoma, superficial spreading melanoma, acral lentiginous melanoma, and lentigo maligna melanoma. [6] On the other hand, nonmelanoma skin cancers, which include basal cell carcinoma (BCC), squamous cell carcinoma (SCC), and sebaceous gland carcinoma (SGC), make up the vast majority of skin cancer cases. [7] These cancers typically develop in the middle and upper layers of the epidermis and are less likely to metastasize, making them easier to treat compared to melanoma.

Common sites for skin cancer include areas frequently exposed to the sun such as the head, face, lips, ears, neck, chest, arms, and hands, and legs in women. However, skin cancer can also occur in less visible areas like the palms, the spaces between fingers and toes, and the genital region. [8] It is important to note that skin cancer can affect anyone, not just those with lighter skin tones. In individuals with darker skin, melanoma more commonly appears on parts of the body that receive less sun exposure, such as the palms and soles.

1.1 Symptoms of Basal Cell Carcinoma

Basal cell carcinoma typically appears on parts of the body exposed to the sun, such as the face and neck. Its symptoms include:

- Pearly or waxy bumps on the skin.
- Flat lesions that resemble scars and can be flesh-colored or brown.
- Sores that bleed or scab over and then reopen.

1.2 Symptoms of Squamous Cell Carcinoma

Squamous cell carcinoma often develops on sun-exposed areas like the face, ears, and hands. In people with darker skin, it can occur on areas less exposed to the sun. Symptoms include:

- Firm, red nodules.
- Flat lesions with a scaly, crusted surface.

1.3 Symptoms and Indicators of Melanoma

Melanoma can develop anywhere on the body, appearing as a new growth or a change in an existing mole. Common sites include the face and trunk in men, and the lower legs in women. It can also develop on previously unblemished skin, even in sun-protected areas. Melanoma symptoms are diverse:

- Changes in an existing mole or the appearance of new spots with irregular borders and varied colors ranging from red to pink, white, blue, or black.
- Itchy or painful lesions.
- Dark patches on the palms, soles, digits, or mucous membranes (e.g., lips, tongue, gums, nose lining, vagina, or anus).

1.4 Symptoms of Rare Skin Cancers

Rare types of skin cancers include:

- **Kaposi's Sarcoma**: Originates in the skin's blood vessels, leading to patches of discolored skin or mucous membranes. It is more prevalent among people with weakened immune systems, such as those with AIDS, or in individuals who have undergone organ transplants. It is also more common among elderly men of Italian or Eastern European Jewish descent, and young men in Africa.
- **Merkel Cell Carcinoma**: This cancer forms hard, shiny nodules either on or just beneath the skin or within hair follicles. It typically affects the head, neck, and trunk.
- **Sebaceous Gland Carcinoma**: Originating in the skin's oil glands, this aggressive cancer often appears on the eyelid as hard, painless nodules and may be initially misidentified.

II. LITRACTURE REVIEW

In this study, we compare the effectiveness of three convolutional neural network (CNN) models: VGG-16, VGG-19, and a custom-built CNN. The models' varying depths were examined to understand their performance impact on the dataset used. Results indicated that VGG-19 is the most precise, achieving an accuracy of 0.9290 and a loss of 1.2842, confirming its reliability for aiding in skin cancer detection [9]. Furthermore, integrating the likelihood of specific skin disorders with differential diagnostic insights from clinic visits accelerates the mastery of diagnostic skills [10]. We employed multiple classification algorithms that analyze features such as color, texture, and morphology of lesions, with the experimental results showing promise [11]. Previous research has successfully applied image classification to differentiate between skin cancer and rashes using CNNs. This approach achieved an average accuracy of 80.2% over 20 epochs [12]. Additionally, we utilized advanced deep learning architectures, ResNet-101 and Inception-v3, for this classification task. The analysis yielded accuracy rates of 84.09% and 87.42% for ResNet-101 and Inception-v3, respectively [13]. The probe, designed and validated through full-wave numerical simulations in CST

Microwave Studio, is effective across all skin types and body locations regardless of skin moisture or thickness [14].

The distribution of the prescribed dosage was confirmed by the uniformity of the 2D and 3D isodose curves in the treatment area, ensuring even application [15]. Our probe, capable of detecting objects at a depth of 0.55 mm with a lateral sensitivity of 0.2 mm, was modeled and validated using a human skin phantom in CST Microwave Studio [16]. Users can consult a real physician by inputting their symptoms into our system, which also allows them to view their test history and receive expert feedback on specific tests based on diagnostic results [17]. This poster aims to evaluate and contrast the performance of two prominent deep learning classification algorithms, CNN and Recurrent Neural Network (RNN), using large datasets from the International Skin Imaging Collaboration (ISIC). The data will be preprocessed and scaled to suit the algorithms, with performance measured by five metrics including ROC [18].

Our research also explores the feasibility of using a Raspberry Pi for deep learning computations, demonstrating its potential in developing affordable, portable devices for screening applications [19]. Mathematical and computational models can significantly aid in early detection, disease prevention, and treatment strategy formulation by simulating skin epidermis behavior in normal and malignant conditions [20]. Additionally, millimeter-wave imaging (MMWI) shows higher reflectivity in malignant areas than in healthy ones, offering a rapid and non-invasive method for early tumor detection and simplifying surgical procedures [21]. This reinforcement learning-based study uses clinical data from skin cancer patients to train a discriminator, aiming to enhance the quality of hyperspectral images of skin through a newly developed generator [22].

III. PROPOSED METHODS

Therefore, early detection is paramount in the treatment of skin cancer [23] [24]. Traditionally, a skin biopsy is employed by physicians to diagnose this disease. This involves removing a sample of tissue from a suspicious lesion to determine whether it is malignant or benign. However, this process can be invasive, slow, and cumbersome. In contrast, computer-aided diagnosis offers a convenient, cost-effective, and rapid alternative. A variety of noninvasive techniques are available to assess whether skin cancer symptoms are indicative of melanoma or another type of skin cancer. The typical steps involved in a computer-based skin cancer detection process are depicted in Figure 1: capturing the image, preprocessing it, segmenting the preprocessed image, extracting relevant features, and classifying the results.

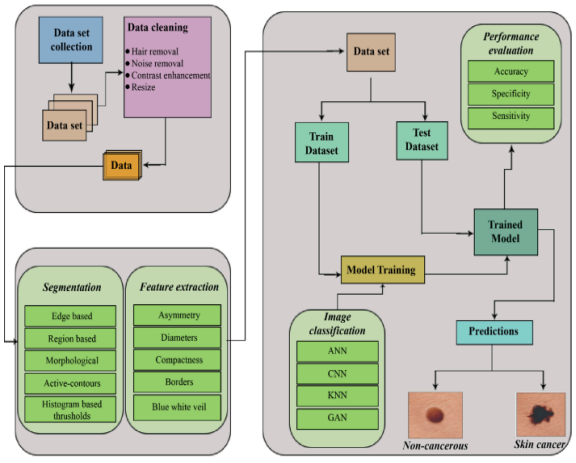

Figure 1 : Proposed process diagram.

Table 1. Specifics on the Suggested Model for CNN

Layer (type)	Output Shape	Parameter
Input Image	128,128,3	0
Convolution	128,128,16	448
ReLU	128,128,16	0
Max-Pooling	64,64,16	0
Convolution	64,64,32	4640
ReLU	64,64,32	0
Max Pooling	32,32,32	0
Convolution	32,32,64	18496
ReLU	32,32,64	0
Max Pooling	16,16,64	0
Dropout	16,16,64	0
Flatten	16384	0
Dense	4	65540
Softmax	4	0

Table 1 displays skin images resized to 128x128 pixels to accommodate the three-hidden-layer CNN model. Each hidden layer incorporates filters that process the image using a 3x3 grid, with output channels of 16, 32, and 64, respectively. The activation of each layer involves ReLU (Rectified Linear Unit) and Max pooling, which helps reduce the image size as shown in Table 1. The process of flattening transforms the image from a multi-dimensional array to a one-dimensional array. Finally, the softmax activation function is utilized to classify the conditions of the skin images as either benign or malignant.

IV. RESULTS AND DISCUSSION

In this section, we present an illustrative example related to skin cancer, demonstrating the application and results of the proposed work.

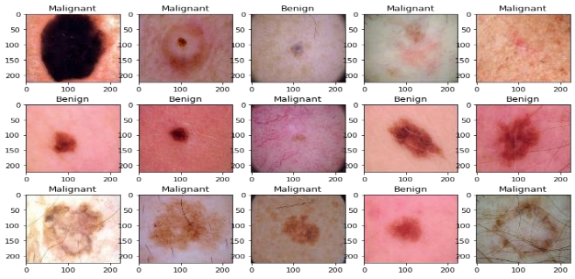

Figure 2 : Illistrative example of skin cancer.

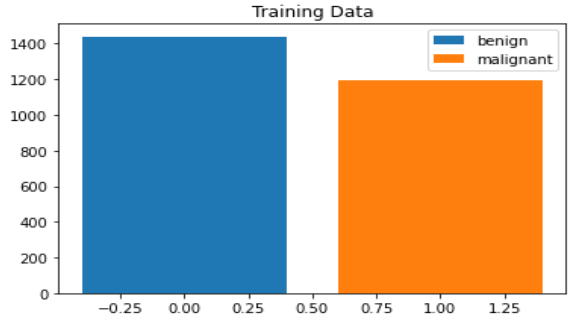

Figure 3 : Shows bening and malignant data during training data

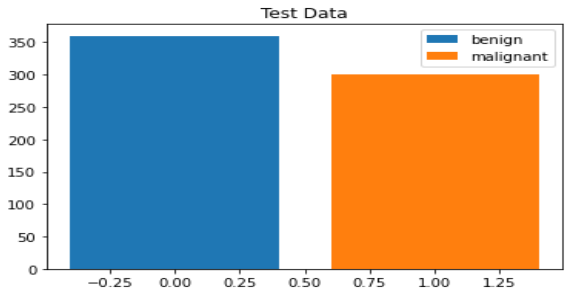

Figure 4 : Shows bening and malignant data during test data

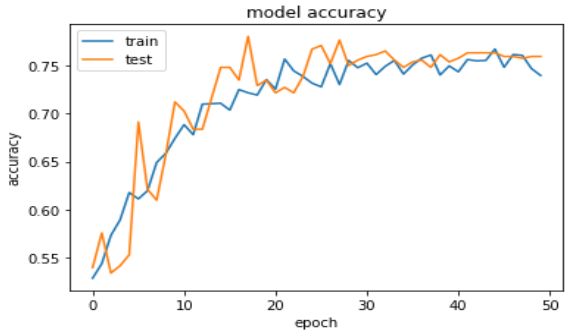

Figure 5 : Shows model accuracy.

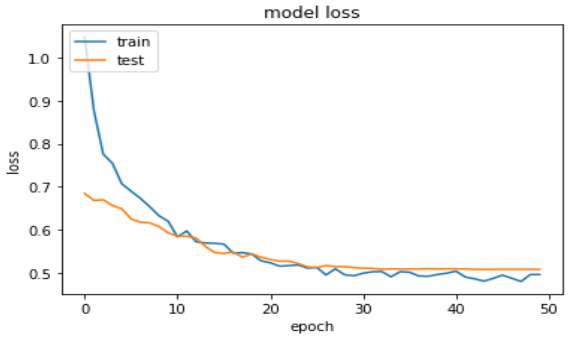

Figure 6 : Shows model loss.

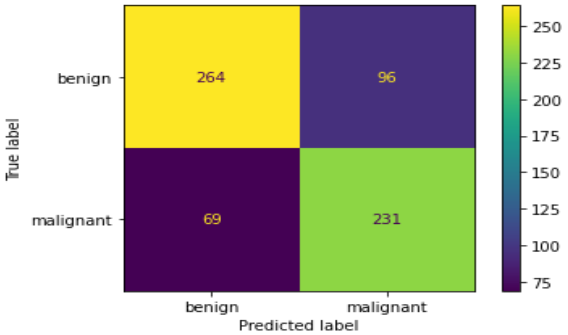

Figure 7 : Shows confusion matrix of proposed work.

Table 2 : Comparison result.

Comparison result		
Method	Accuracy	Loss
VGG-16, VGG-19	92.9	1.2842
CNN	76	2.5634
CNN , RNN	86	2.4532
MobileNetV2	89	1.8654
Proposed	93	0.4965

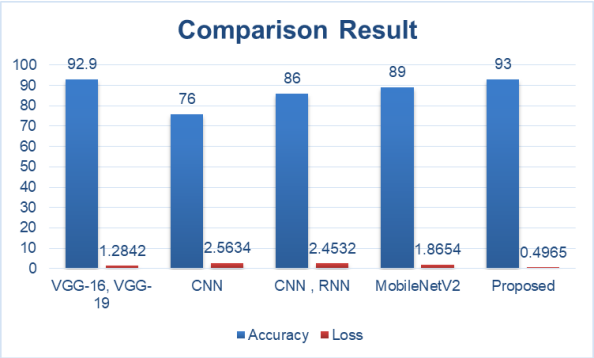

Figure 8 : Comparison result

V. CONCLUSION

Digital image processing has been employed to develop an automated method for distinguishing between various skin conditions, including dermatofibroma, nevus pigmentosus, squamous cell carcinoma, and melanoma. The convolutional neural network (CNN) model used in this study features three hidden layers, each with a 3x3 filter size, producing outputs of 16, 32, and 64 channels respectively. The model includes a fully connected layer and uses softmax activation with a total input of 64 channels. Optimization of the model is achieved using various methods such as SGD, RMSprop, Adam, and Nadam. During testing, the CNN model utilizing the Adam optimizer achieved a high level of performance, with an accuracy of 93%, a loss of 0.4965, and strong precision and recall metrics. This demonstrates its efficacy in accurately differentiating between malignant skin cancers and benign tumor lesions within the dataset.

Relevant conflicts of interest/financial disclosures: The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

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