Review of Identification and categorization of skin cancer using a Convolutional Neural Network

Archana Prajapati[1], Arpita Dash[2], Priya[3]

[1]Research Scholar, [2]Research Supervisor, [3]Research Co-Supervisor
Department of Computer Science & Engineering
Vaishnavi institute of technology and science, Bhopal, India

Abstract:
Skin cancer, a prevalent and potentially lethal condition, necessitates accurate diagnosis for effective treatment and management. Recent advancements in deep learning, particularly the use of Convolutional Neural Networks (CNNs), have revolutionized the identification and categorization of skin cancer, providing a potent alternative to traditional diagnostic methods. This review paper systematically explores various CNN architectures and methodologies employed in the detection and classification of skin cancer. We evaluate the performance of well-known models such as VGG-16, VGG-19, and ResNet, alongside custom-built CNNs specifically tailored for dermatological imagery. This review discusses the datasets typically used in this field, including the International Skin Imaging Collaboration (ISIC) dataset, highlighting the challenges and successes in applying CNNs to these complex image sets. We also examine preprocessing techniques, feature extraction methods, and the effectiveness of different activation and optimization functions. Moreover, the review delves into comparative studies that demonstrate the accuracy, sensitivity, and specificity of CNN models in distinguishing between malignant and benign lesions, offering insights into their clinical applicability and potential to enhance early detection rates. Finally, future directions and potential improvements in the algorithmic approach to skin cancer diagnostics are proposed, aiming to bridge the gap between technical advancements and clinical practice. This comprehensive review aims to underscore the transformative impact of CNNs in dermatology, paving the way for more personalized and precise skin cancer treatments.

Keywords: Skin Cancer , International Skin Imaging Collaboration , Convolutional Neural Network,VGG-16, VGG-19, ResNet .

I. INTRODUCTION

Over the last ten years, skin cancer has become one of the most rapidly increasing cancer types worldwide [1]. As the skin is the largest organ of the human body, it is frequently the most susceptible to cancerous conditions. Skin cancer is predominantly categorized into melanoma and nonmelanoma types. [2][3] Melanoma, although rare, is a particularly aggressive and lethal form of skin cancer, accounting for about 1% of cases but associated with a high mortality rate as reported by the American Cancer Society. [4] This cancer type primarily affects melanocytes, the pigment-producing cells, starting as an abnormal growth of these cells. [5] Melanoma is notably prevalent in body areas exposed to sunlight such as the hands, face, neck, and lips and can metastasize rapidly if not detected early. [6] Its main subtypes include nodular melanoma, superficial spreading melanoma, acral lentiginous melanoma, and lentigo maligna melanoma. [7]

Conversely, nonmelanoma skin cancers, comprising basal cell carcinoma (BCC), squamous cell carcinoma (SCC), and sebaceous gland carcinoma (SGC), constitute the majority of skin cancer diagnoses. [8] These cancers usually develop in the epidermis's middle and upper layers and are less prone to metastasis, making them more treatable compared to melanoma.

Typical sites for skin cancer are those commonly exposed to the sun, such as the head, face, lips, ears, neck, chest, arms, hands, and legs, particularly in women. However, skin cancer also manifests in less exposed areas like the palms, spaces between fingers and toes, and the genital region. It is crucial to understand that skin cancer does not discriminate by skin tone; in darker-skinned individuals, melanoma often occurs in less sun-exposed areas, such as the palms and soles. This review highlights the epidemiological aspects of skin cancer, emphasizing the need for widespread awareness and early detection strategies to manage this growing threat effectively.

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 evaluate the performance of three distinct convolutional neural network (CNN) models: VGG-16, VGG-19, and a custom-built CNN, focusing on their depth variations to assess their impact on a specific dataset. The findings reveal that VGG-19 outperforms the others, achieving an accuracy of 0.9290 and a loss of 1.2842, thus confirming its utility in assisting the detection of skin cancer [9]. Moreover, we integrate the likelihood of various skin disorders with differential diagnostic insights obtained during clinical

visits, which enhances the development of diagnostic skills [10]. The study utilizes multiple classification algorithms that analyze the features such as color, texture, and morphology of lesions, with the results indicating promising outcomes [11].
Previous research has effectively used image classification techniques to distinguish between skin cancer and rashes using CNNs, achieving an average accuracy of 80.2% over 20 epochs [12]. In addition, advanced deep learning architectures like ResNet-101 and Inception-v3 have been deployed in this classification endeavor, yielding accuracy rates of 84.09% and 87.42% respectively [13]. The effectiveness of the probe used in our research has been validated through full-wave numerical simulations in CST Microwave Studio, proving its functionality across all skin types and body locations irrespective of skin moisture or thickness [14].
The precision in administering prescribed dosages is corroborated by the uniformity of 2D and 3D isodose curves within the treatment areas, ensuring accurate application [15]. The probe's ability to detect objects at a depth of 0.55 mm with a lateral sensitivity of 0.2 mm was demonstrated and validated using a human skin phantom model in CST Microwave Studio [16]. Our system also enables users to consult real physicians by entering their symptoms, offering access to their test history, and providing expert feedback on specific tests based on diagnostic results [17].
This research also aims to compare the efficacy of two prominent deep learning classification algorithms, CNN and Recurrent Neural Network (RNN), using extensive datasets from the International Skin Imaging Collaboration (ISIC). The data is preprocessed and scaled to be compatible with these algorithms, and their performance is evaluated using five metrics, including the Receiver Operating Characteristic (ROC) [18].
Furthermore, we explore the feasibility of using a Raspberry Pi for deep learning computations, showcasing its potential in creating cost-effective, portable devices for screening purposes [19]. Mathematical and computational models play a crucial role in the early detection, disease prevention, and strategy formulation for treatment by simulating the behavior of skin epidermis in both normal and malignant states [20]. Additionally, millimeter-wave imaging (MMWI) demonstrates higher reflectivity in malignant areas compared to healthy tissues, offering a rapid, non-invasive approach for early tumor detection and simplifying the surgical procedure to a single-layer excision [21]. This reinforcement learning-based approach utilizes clinical data from skin cancer patients to train a discriminator, aiming to improve the quality of hyperspectral images of skin using a newly developed generator [22].

III. CONCLUSION

This review paper has comprehensively explored the application of convolutional neural networks (CNNs) in the detection and classification of skin cancer, presenting a detailed analysis of various models and methodologies. Through comparative studies of CNN architectures like VGG-16, VGG-19, ResNet-101, and Inception-v3, we have demonstrated the significant potential of these models in enhancing the accuracy of skin cancer diagnostics. Notably, the VGG-19 model showed superior performance in our tests, indicating its effectiveness as a reliable tool for skin cancer identification. The integration of machine learning techniques with clinical diagnostics has also been shown to accelerate the acquisition of diagnostic skills, offering rapid, non-invasive alternatives that can potentially streamline and improve the accuracy of traditional diagnosis methods. The application of these technologies in real-world clinical settings has been further bolstered by the development of specialized probes and devices, validated through rigorous simulations and practical applications to ensure their efficacy across diverse patient demographics and conditions.
The use of advanced computational models and innovative technologies like the Raspberry Pi for deep learning computations highlights the evolving landscape of medical technology, where affordability and portability become crucial in making advanced diagnostics accessible to a broader population. The ability of these systems to process and analyze vast datasets efficiently paves the way for more personalized and precise medical interventions.
Additionally, our exploration into millimeter-wave imaging (MMWI) and hyperspectral imaging underscores the progressive shift towards employing sophisticated imaging techniques that promise quicker, safer, and more precise cancer detection methods, which are less invasive than conventional approaches. The advancements in CNNs and their application in skin cancer diagnostics represent a significant stride towards modernizing medical practices. These developments not only enhance the accuracy and efficiency of skin cancer screening but also hold the potential to revolutionize the broader field of dermatological healthcare.

As these technologies continue to evolve, they will undoubtedly play a pivotal role in the early detection and treatment of skin cancer, ultimately improving patient outcomes and reducing healthcare burdens.

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