Santara Chouhan, 2024, 12:3
ISSN (Online): 2348-4098
ISSN (Print): 2395-4752

International Journal of Science, Engineering and Technology

An Open Access Journal

Enhanced Skin Cancer Diagnosis and Classification Using Convolutional Neural Network Models

Research Scholar Santara Chouhan, Professor Jitendra Khaire
Department of Computer Science & Engineering
Patel College of Science & Technology, Indore, India

Abstract- Skin cancer is a prevalent and dangerous condition that poses significant health risks to individuals. Early detection is critical for the effective treatment of skin cancer, as it is for other types of cancer. However, traditional methods of diagnosing skin cancer have demonstrated low accuracy rates and frequently lead to unnecessary examinations. Additionally, many existing machine learning models for cancer detection are limited in the number of skin cancer categories they can identify, which restricts their effectiveness. This research introduces a system that leverages Convolutional Neural Networks (CNNs) to automatically identify skin cancer and benign tumor lesions. The proposed model includes three hidden layers with output channels of 16, 32, and 64, respectively. It operates with a learning rate of 0.001 and employs various optimizers, including Stochastic Gradient Descent (SGD), RMSprop, Adam, and Nadam. Among these, the Adam optimizer delivers the best performance, achieving an accuracy rate of 93% in classifying skin lesions as either benign or malignant, based on the ISIC dataset. The results of this research surpass the accuracy of currently employed skin cancer classification methods. By utilizing the ISIC dataset, the findings demonstrate significant improvements in the detection and classification of skin cancer, offering a more reliable and efficient alternative to traditional diagnostic techniques. programs are essential for minimizing waterborne diseases and enhancing residents' quality of life.

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

I. INTRODUCTION

Over the past decade, skin cancer has become one of the fastest-growing types of cancer. As the skin is the body's largest organ, it is also the most commonly affected by cancer. There are two primary types of skin cancer: melanoma and nonmelanoma [1].

Melanoma is a highly dangerous, rare, and potentially fatal form of skin cancer. According to the American Cancer Society, melanoma accounts for only about 1% of all skin cancer cases but has a significantly higher mortality rate. Melanoma primarily affects melanocytes, the cells responsible for producing melanin [2]. The initial cause is the abnormal growth of these normally functioning cells. Melanoma can develop on any part of the body, with common sites including the hands, face, neck, and lips, especially in areas with high sun exposure [3]. Early detection is crucial for curing melanoma; otherwise, it can metastasize and lead to fatal outcomes. Subtypes of melanoma include nodular melanoma, superficial spreading melanoma, acral lentiginous melanoma, and lentigo maligna [4]. Nonmelanoma skin cancers, including basal cell carcinoma (BCC), squamous cell carcinoma (SCC), and sebaceous gland carcinoma

(SGC), constitute the majority of skin cancer diagnoses [5]. These cancers develop in the middle and upper layers of the epidermis and have a low likelihood of metastasizing. Unlike melanoma, nonmelanoma cancers are generally easier to treat [6]. The most common areas for skin cancer to develop include the head, face, lips, ears, neck, chest, arms, and hands, as well as the legs in women, due to sun exposure. However, skin cancer can also appear in less visible places such as the palms, the spaces between fingers and toes, and the genital region. Anyone can develop skin cancer, regardless of skin tone [7]. While melanoma is more common in individuals with lighter skin, it also occurs in people with darker skin tones, often appearing on parts of the body less frequently exposed to sunlight, such as the palms and soles [8]. The rising incidence of skin cancer highlights the need for increased awareness and early detection. Regular skin checks and protective measures against sun exposure can significantly reduce the risk and improve treatment outcomes.

Symptoms of Skin Cancer

Basal Cell Carcinoma (BCC)

Basal cell carcinoma often appears on sun-exposed areas such as the face and neck. Symptoms include:

- Pearly or waxy lumps
- Flat, flesh-colored, or brown scar-like lesions
- Sores that bleed or scab over and reopen
- Squamous Cell Carcinoma (SCC)

Squamous cell carcinoma usually develops on sun-exposed areas like the face, ears, and hands. Symptoms include:

- Hard, red nodules
- Scaly, crusted surface lesions

Melanoma

Melanoma can occur anywhere on the body, often as a new growth or a change in an existing mole. In men, it is frequently found on the face and trunk, while in women, it appears more often on the lower legs. Symptoms include:

- Dark spots spreading over a brown background
- Lesions with irregular borders and varying colors (red, pink, white, blue, black)
- Painful or itchy sores
- Dark patches on palms, soles, fingers, toes, lips, gums, and other mucous membranes

Kaposi's Sarcoma: Kaposi's sarcoma is an uncommon cancer that originates in the skin's blood vessels, leading to discolored patches on the skin or mucous membranes. It is more prevalent in individuals with compromised immune systems, such as those with AIDS or organ transplant recipients, elderly men of Italian or Eastern European Jewish descent, and young men in Africa.
Merkel Cell Carcinoma: Merkel cell carcinoma presents as hard, shiny nodules on or just beneath the skin, often in hair follicles. It typically affects the head, neck, and trunk.

Sebaceous Gland Carcinoma: This aggressive cancer arises from the skin's oil glands, often manifesting as hard, painless nodules on the eyelids, and is frequently misdiagnosed.

Early identification and diagnosis of skin cancer are essential for effective treatment and improving survival rates. Public awareness and regular skin checks can significantly aid in catching the disease in its initial stages, thereby enhancing the chances of successful treatment.

II. LITRACTURE REVIEW

VGG-16, VGG-19, and a custom-built CNN model are evaluated against one another. Since there is a discrepancy between the three models' depths, we also investigated how that affects a model's performance within the context of the dataset we employed. According to the findings of the tests, VGG-19 is the most accurate model, with a score of 0.9290 for accuracy and a loss of 1.2842, making it a trustworthy tool for assisting in the identification of skin cancer [9].

Knowing the likelihood of certain skin disorders and comparing it with the differential diagnostic information gained from the visiting staff during the clinic helps swiftly develop expertise in the art of diagnosis [10].

To anticipate the classes, we employ several classification algorithms using features collected from the lesion's many properties, such as its color, texture, and skeleton. The experimental outcomes are generally encouraging [11].

Previous studies have shown success in utilizing image classification to categorize various forms of skin cancer; this method use CNN[Convolutional neural network] to identify and discriminate skin cancer pictures from rash images, before categorizing them accordingly. The model achieved an average accuracy of 80.2% across 20 epochs [12] when classifying images as either skin cancer afflicted images or rashes images.

For this categorization work, we use the deep learning architectures ResNet-101 and Inception-v3. Analyzing the gathered findings reveals an accuracy rate of 84.09% in ResNet-101 architecture and an accuracy rate of 87.42% in Inception-v3 architecture [13].

Regardless of the skin's moisture state or thickness, the probe is guaranteed to work for all people and body locations. Full-wave numerical simulations in CST Microwave Studio [14] were used to realize and validate the design.

Because of this, the prescribed dosage was administered evenly to the afflicted region, as shown by the flatness of the 2D isodose curves and 3D isodose surfaces at the desired distances from the plane of the active sites inside the applicator [15].

The suggested instrument can detect objects at a depth of 0.55 mm with a lateral sensitivity of 0.2 mm. The probe was modeled in CST Microwave Studio, built in a phantom of human skin, and confirmed by measurements [16].

Users may also get in touch with a real doctor by putting in their symptoms. In addition, the user's test history may be seen in the personal area, and the user can get expert input on a specific test based on the skin problem's diagnostic findings [17].

The purpose of this poster is to examine and compare two popular deep learning classification algorithms, the Convolutional Neural Network (CNN) and the Recurrent Neural Network (RNN), and to put them through their paces using large data sets from the International Skin Imaging Collaboration (ISIC) archive. Moreover, raw datasets from ISIC will be preprocessed and scaled to make the data algorithm-friendly. Also, five metrics, including ROC [18], will be used to evaluate and compare the performance of these methods.

As a result of our investigation, we learned that a Raspberry Pi can be used to power intensive computations like deep learning, and that this powerful computing power may then be bundled into a cheap portable device for use in screening [19].

Early detection, disease prevention, and treatment strategy selection may all benefit from mathematical and computational models of skin epidermis modulation in both the normal and malignant states [20].

Moreover, the values of millimeter-wave reflectivity are observed to be much greater for malignant regions compared to healthy regions. Due to the fact that MMWI does not call for the processing or staining of tissue, it may be conducted quickly, allowing for the detection of tumors at an early stage and reducing the complexity of the tumor removal operation to a single-layer excision technique [21].

Both models get rewards or punishments according on how well they perform, making this a reinforcement learning model. We utilize clinical measurements from patients with skin cancer to train the discriminator. The purpose of this research is to create a generator that may be used to improve the quality of hyperspectral images of skin cancer [22].

III. PROPOSED METHODS

Therefore, early detection is crucial for treating skin cancer [23]. A skin biopsy is the standard approach used by doctors to diagnose skin cancer. The purpose of this treatment is to get a tissue sample from a suspicious skin lesion for further medical investigation to establish malignant or noncancerous status. This is a difficult, sluggish, and lengthy procedure. Diagnosing skin cancer with the use of a computer is convenient, inexpensive, and quick. There are a variety of noninvasive methods offered for determining if the symptoms of skin cancer are caused by melanoma or another kind of skin cancer.

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's skin pictures are reduced to 128 pixels by 128 pixels so the 3-hidden-layer CNN model may utilize them. Each of the hidden layers includes filters that alter the image in a 3x3 grid, with 16, 32, or 64 output channels. Each layer's activation uses Rel-U and Max pooling. Table1 show how Maxpooling reduces image size. Flattening decreases picture depth to one dimension. The softmax activation function will be used to classify skin image conditions as benign or malignant.

IV. RESULT & DISCUSSION

In this section explain about skin cancer illistrative example with result related proposed work.

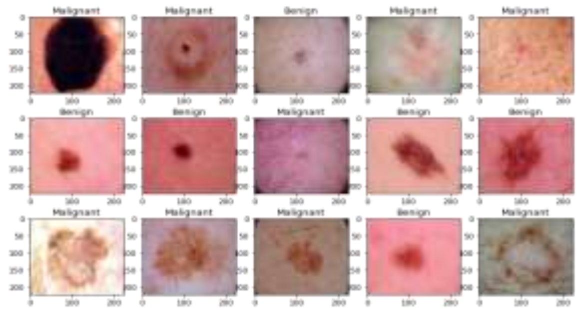

Figure 2: Illistrative example of skin cancer.

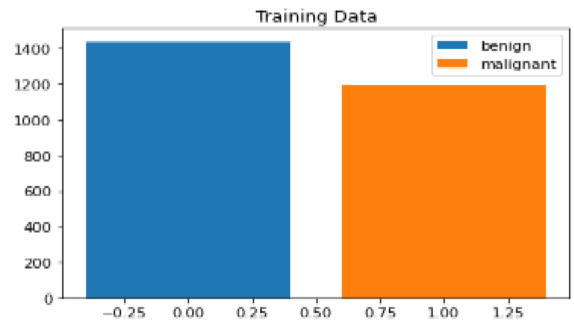

Figure 3: Shows bening and malignant data during training data

Figure 4: Shows bening and malignant data during test data

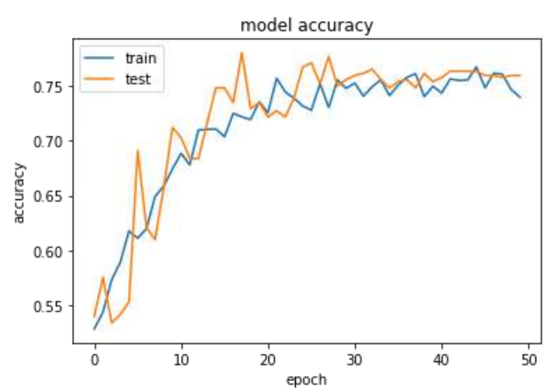

Figure 5: Shows model accuracy.

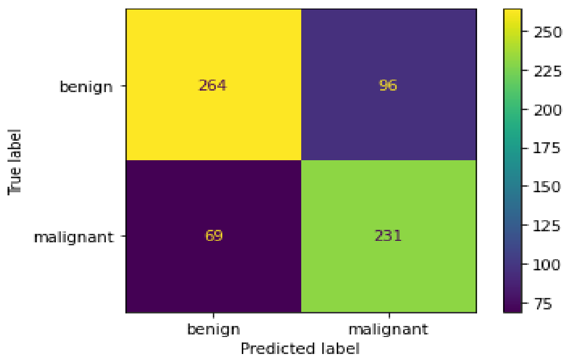

Figure 6: Shows confusion matrix of proposed work.

V. CONCLUSION

Digital image processing was employed to develop an automated method for distinguishing between derma to fibroma, nevus pigmentosus, squamous cell carcinoma, and melanoma. The convolutional neural network (CNN) model used in this research includes three hidden layers, each with a filter size of three, producing outputs of 16, 32, and 64 channels, respectively. Additionally, the model features a fully connected layer, softmax activation, and a total of 64 input channels.

To optimize the proposed model, various optimizers were utilized, including SGD, RMSprop, Adam, and Nadam. In our tests, the CNN model optimized with Adam achieved the highest performance, with an accuracy of 93%, a loss of 0.4965, and high values for precision and recall. This makes it the most effective method for differentiating between skin cancer and benign tumor lesions within the dataset.

REFERENCES

1. B. Bılgıç, "Comparison of Breast Cancer and Skin Cancer Diagnoses Using Deep Learning Method," 2021 29th Signal Processing and Communications Applications Conference (SIU), 2021, pp. 1-4, doi: 10.1109/SIU53274.2021.9477992.
2. A. Mirbeik-Sabzevari and N. Tavassolian, "Ultrawideband, Stable Normal and Cancer Skin Tissue Phantoms for Millimeter-Wave Skin Cancer Imaging," in IEEE Transactions on Biomedical Engineering, vol. 66, no. 1, pp. 176-186, Jan. 2019, doi: 10.1109/TBME.2018.2828311.
3. C. Aydinalp, S. Joof, T. Yilmaz, N. P. Özsobaci, F. A. Alkan and I. Akduman, "In Vitro Dielectric Properties of Rat Skin Tissue for Microwave Skin Cancer Detection," 2019 International Applied Computational Electromagnetics Society Symposium (ACES), 2019, pp. 1-2.
4. H. Younis, M. H. Bhatti and M. Azeem, "Classification of Skin Cancer Dermoscopy Images using Transfer Learning," 2019 15th International Conference on Emerging Technologies (ICET), 2019, pp. 1-4, doi: 10.1109/ICET48972.2019.8994508.
5. Y. Jusman, I. M. Firdiantika, D. A. Dharmawan and K. Purwanto, "Performance of Multi Layer Perceptron and Deep Neural Networks in Skin Cancer Classification," 2021 IEEE 3rd Global Conference on Life Sciences and Technologies (LifeTech), 2021, pp. 534-538, doi: 10.1109/LifeTech52111.2021.9391876.
6. A. W. Setiawan, "Effect of Color Enhancement on Early Detection of Skin Cancer using Convolutional Neural Network," 2020 IEEE International Conference on Informatics, IoT, and Enabling Technologies (ICIoT), 2020, pp. 100-103, doi: 10.1109/ICIoT48696.2020.9089631.
7. A. W. Setiawan, A. Faisal and N. Resfita, "Effect of Image Downsizing and Color Reduction on Skin Cancer Pre-screening," 2020 International Seminar on Intelligent Technology and Its Applications (ISITIA), 2020, pp. 148-151, doi: 10.1109/ISITIA49792.2020.9163734.
8. H. K. Kondaveeti and P. Edupuganti, "Skin Cancer Classification using Transfer Learning," 2020 IEEE International Conference on Advent Trends in Multidisciplinary Research and Innovation (ICATMRI), 2020, pp. 1-4, doi: 10.1109/ICATMRI51801.2020.9398388.
9. P. Zhu, "Convolutional Neural Networks Based Study and Application for Multicategory Skin Cancer Detection," 2022 3rd International Conference on Electronic Communication and Artificial Intelligence (IWECAI), 2022, pp. 558-561, doi: 10.1109/IWECAI55315.2022.00114.

10. C. H. Chang, W. En Wang, F. Y. Hsu, R. Jhen Chen and H. C. Chang, "AI HAM 10000 Database to Assist Residents in Learning Differential Diagnosis of Skin Cancer," 2022 IEEE 5th Eurasian Conference on Educational Innovation (ECEI), 2022, pp. 1-3, doi: 10.1109/ECEI53102.2022.9829465.
11. M. A. Sabri, Y. Filali, H. El Khoukhi and A. Aarab, "Skin Cancer Diagnosis Using an Improved Ensemble Machine Learning model," 2020 International Conference on Intelligent Systems and Computer Vision (ISCV), 2020, pp. 1-5, doi: 10.1109/ISCV49265.2020.9204324.
12. S. Subha, D. C. J. W. Wise, S. Srinivasan, M. Preetham and B. Soundarlingam, "Detection and Differentiation of Skin Cancer from Rashes," 2020 International Conference on Electronics and Sustainable Communication Systems (ICESC), 2020, pp. 389-393, doi: 10.1109/ICESC48915.2020.9155587.
13. A.Demir, F. Yilmaz and O. Kose, "Early detection of skin cancer using deep learning architectures: resnet-101 and inception-v3," 2019 Medical Technologies Congress (TIPTEKNO), 2019, pp. 1-4, doi: 10.1109/TIPTEKNO47231.2019.8972045.
14. G. Mansutti, A. T. Mobashsher and A. Abbosh, "Design of a Millimeter-Wave Near-Field Probe for Early-Stage Skin Cancer Detection," 2019 13th European Conference on Antennas and Propagation (EuCAP), 2019, pp. 1-4.
15. H. Badry, L. Oufni, H. Ouabi, R. Rabi and H. Iwase, "Dose optimization of high dose rate brachytherapy for skin cancer treatment using Harrison-Anderson-Mick applicator," 2020 IEEE 6th International Conference on Optimization and Applications (ICOA), 2020, pp. 1-5, doi: 10.1109/ICOA49421.2020.9094522.
16. G. Mansutti, A. T. Mobashsher, K. Bialkowski, B. Mohammed and A. Abbosh, "Millimeter-Wave Substrate Integrated Waveguide Probe for Skin Cancer Detection," in IEEE Transactions on Biomedical Engineering, vol. 67, no. 9, pp. 2462-2472, Sept. 2020, doi: 10.1109/TBME.2019.2963104.
17. Aruhan, "A Medical Support Application for Public based on Convolutional neural network to Detect Skin Cancer," 2021 IEEE International Conference on Computer Science, Electronic Information Engineering and Intelligent Control Technology (CEI), 2021, pp. 253-257, doi: 10.1109/CEI52496.2021.9574496.
18. A. Kumar, A. Kapelyan and A. K. Vatsa, "Classification of Skin Phenotype: Melanoma Skin Cancer," 2021 IEEE Integrated STEM Education Conference (ISEC), 2021, pp. 247-247, doi: 10.1109/ISEC52395.2021.9763999.
19. C. Jen Ngeh, C. Ma, T. Kuan-Wei Ho, Y. Wang and J. Raiti, "Deep Learning on Edge Device for Early Prescreening of Skin Cancers in Rural Communities," 2020 IEEE Global Humanitarian Technology Conference (GHTC), 2020, pp. 1-4, doi: 10.1109/GHTC46280.2020.9342911.
20. M. Saidalieva, M. Hidirova and A. Shakarov, "Mathematical Model Of Skin Epidermis Regulatory Mechanisms in Squamous Cell Cancers Development," 2020 International Conference on Information Science and Communications Technologies (ICISCT), 2020, pp. 1-4, doi: 10.1109/ICISCT50599.2020.9351472.
21. A. Mirbeik-Sabzevari, E. Oppelaar, R. Ashinoff and N. Tavassolian, "High-Contrast, Low-Cost, 3-D Visualization of Skin Cancer Using Ultra-High-Resolution Millimeter-Wave Imaging," in IEEE Transactions on Medical Imaging, vol. 38, no. 9, pp. 2188-2197, Sept. 2019, doi: 10.1109/TMI.2019.2902600.
22. L. Annala, N. Neittaanmäki, J. Paoli, O. Zaar and I. Pölönen, "Generating Hyperspectral Skin Cancer Imagery using Generative Adversarial Neural Network," 2020 42nd Annual International Conference of the IEEE Engineering in Medicine & Biology Society (EMBC), 2020, pp. 1600-1603, doi: 10.1109/EMBC44109.2020.9176292.
23. Premier Surgical Staff. What Is the Difference between Melanoma And non-Melanoma Skin Cancer? PSS. Available online: https://www.premiersurgical.com/01/whats-the-difference-between-melanoma-and-non-melanoma-skin-cancer/ (accessed on 6 February 2021)
24. https://www.isic-archive.com/#!/topWithHeader/wideContentTop/main