RESEARCH ARTICLE OPEN ACCESS

Spotting Skin Cancer using CNN

P.Harsha[1],Garipelly Sahruthi[2], Anampally Vaishnavi[3], Pokala Varshini[4]
1(Malla Reddy Engineering College for Women (Autonomous), Hyderabad, India
Email: harsha.renu@gmail.com)
2(Malla Reddy Engineering College for Women (Autonomous), Hyderabad, India
Email:sahgrply@gmail.com)
3(Malla Reddy Engineering College for Women (Autonomous), Hyderabad, India
Email: anampallyvaishnavi9@gmail.com)
4(Malla Reddy Engineering College for Women (Autonomous), Hyderabad, India
Email:pokalavarshini14@gmail.com)

Abstract:
The development of machine learning has changed many aspects of our life, including how we detect skin malignancies. The most grave kind of skin disease is melanoma, a sort of skin cancer. Medical specialists can treat it, but doing so requires skill and experience. The cancer's stage and the patient's current health condition will determine how the patient is treated. Therefore, SKIN CANCER SPOTTING USING CNN is introduced in order to quickly detect these forms of skin tumours. Modern medical image processing techniques examine images obtained from the skin and images captured under a microscope using a variety of algorithms. The lamination of the excavated structures is done using a Convolutional Neural Network classifier namely based on deep learning. We are experts in convolutional neural networks and have achieved 99.8% prediction accuracy.

***Keywords*:** Data augmentation, Convolutional neural network, Melanoma, malignant, benign, dataset visualization, optimizer, rel-U. Hyperparameter. Convolutional layer

I. INTRODUCTION

To detect melanoma skin cancer, a multiclass classification model based on a unique convolutional neural network in tensor flow must be developed. to create a CNN-based melanoma detection model. Melanoma is a skin condition that can be fatal if it is not caught early. A survey indicates that 75% of skin cancer deaths are caused by the disease. This is the greatest method for analyzing the photos and warning patients and doctors about the possibility of melanoma skin cancer [6]. A significant portion of the manual work required for diagnosis might be eliminated by this detecting technology. Convolutional neural networks, a arrangement of artificial

II. LITERATURE SURVEY

CNN was used to identify skin cancer in early study on skin disorders including as melanoma, naevus, and seborrheic keratosis. We have incorporated 9 skin disorders in our system: Melanoma, Actinic Keratosis, Basal Cell Carcinoma, Dermatofibroma, Pigmented Benign Keratosis, Seborrheic Keratosis, Squamous Cell Carcinoma, Vascular Lesion, and Nevus. As a result, as compared to previous detection systems, this article contains a greater variety of disorders. In comparison to other systems, the developed code is user-friendly and easy to access. Dermatologists can quickly grasp the results, which can be determined with pinpoint accuracy in a fraction of a second. The quality of a dataset determines how accurate CNN training is. Here, we added a sizable number of images to the dataset and further categorized them into diseases. Based on the classes that can be used for classification, the labels are taken into account. It is a quick and early detection that increases the likelihood of recovery.

III. METHODOLOGY

A dataset with various photos of skin conditions must be created. The International Skin Imaging Collaboration created the collection, which includes 2357 photos of both malignant and benign oncological illnesses (ISIC). The pictures were classified using the ISIC system, and subgroups with the identical sum of pictures were created by the exemption of melanoma and moles, where those images dominated. Actinic keratosis, basal cell carcinoma, dermatofibroma, melanoma, nevus, pigmented benign keratosis, and seborrheic keratosis are among the 9 subsets that make up the dataset. Vascular lesion, Squamous cell cancer. The tasks that should be performed are:

1. Reading and comprehending data.
2. Dataset Creation: Create a train and validation dataset with a batch size of 32 from the train directory. The photos should also be resized to 180*180.

3. Dataset visualization: displaying a single instance from each of the dataset's nine subsets.
4. Model development and instruction: Construct a CNN model that can identify the 9 classes that are present in the dataset. The model resizes photos as construction is underway to equalize the pixel values (0,1). Select an appropriate optimizer and loss function for training the model.
5. Model construction and training using the enhanced data: Make a CNN model that can recognize the 9 classes in the current dataset. The data will be created using several models in this step. Existing data is displayed from all possible angles, preventing misunderstanding during the image-detection process. Rescale photos to equalize pixel values between while generating the model (0,1). Select the best optimizer, data augmentation technique, loss function, and model for training.

IV. IMPLEMENTATION

The connectivity pattern between its neurons is triggered by the visual cortex in convolutional neural networks, which are a superior sort of feed-forward artificial neural network. Convolutional neural networks, often known as convents, are simply neural networks with shared parameters. CNN does not require any pre-processing and may be applied directly to an underexposed image. The convolutional layer, a specific kind of layer, is what gives convolutional neural networks their strength. CNN's design is similar to that of general-purpose neural networks; its neurons play roles in weight, partiality, and activation.

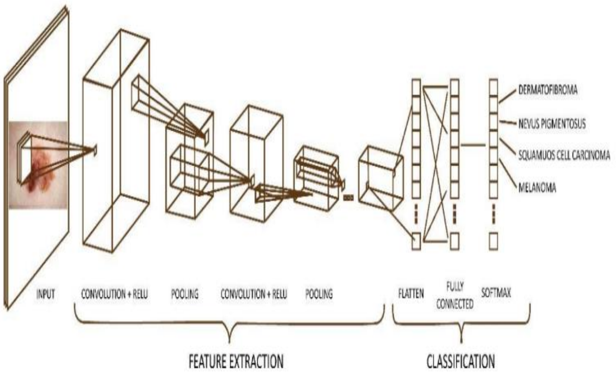

Figure-1 Convolution Layer

i)Convolutional layer:
The convolution process at the convolution layer is principally responsible for CNN. The convolution layer is the initial layer that processes the picture as an input system model. The picture will be convoluted using a filter to eliminate features from the participation image, commonly known as the feature map.

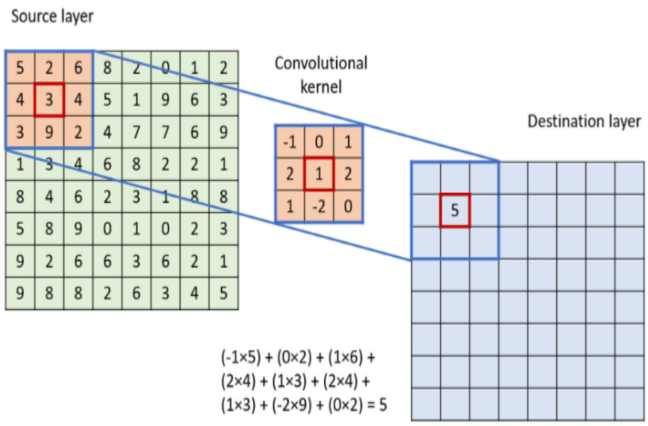

Figure.2-Illustration of Convolutional process.

ii)Activation Rel-U:
In the CNN method, polling layers are commonly implanted after many convolution layers. The pooling layer has a number of benefits, including the ability to control over-fitting by gradually decreasing the output volume on the feature map. Data is decreased at the pooling layer by employing mean pooling or maximum pooling. While the maximum pooling chooses the highest value, the mean-pooling determines the average value.

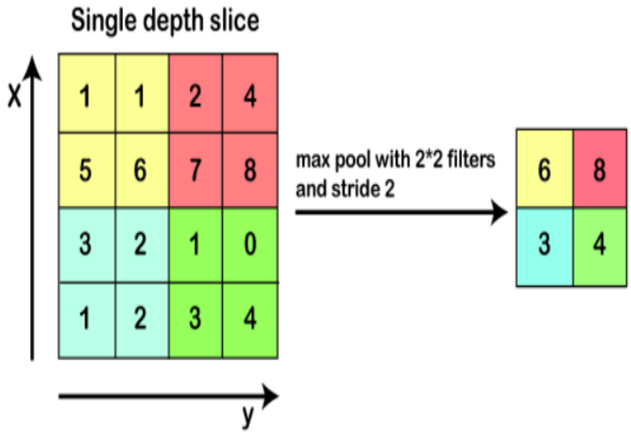

Figure.3- Pooling Process.

iii)Fully Connected Layer:
In the multilayer perceptron architecture, the Fully-Connected layer is the final layer. All of the neurons from the preceding activation layer will be connected by this layer. In this phase, all input layer neurons must be converted into one-dimensional data.

iv)Hyperparameter:
The performance of the model trains can be impacted by the hyperparameter, which has changing values that persist during the model training process. Different model training algorithms call for various hyperparameters, whereas some straight forward algorithms call for none.

TABLE.1- PERFORMANCE DETAILS ABOUT THE PROPOSED MODEL

Class	Precision	Recall	F1-Score	No. of Images
Melanoma	0.98	0.98	0.98	242
Actinic keratosis	1.00	1.00	1.00	338
Basal Cell carcinoma	0.98	0.98	0.98	352
Dermatofibroma	1.00	1.00	1.00	257
Pigmented benign keratosis	0.97	0.97	0.97	351
Seborrheic keratosis squamous cell carcinoma	1.00	1.00	1.00	255
Vascular lesion	0.98	0.98	0.98	316
Nevus	0.98	0.98	0.98	246

V. RESULTS

The specifics of the training and the outcomes will be the ensuing portion. Training, which comprises 80% of the whole data, and testing, which comprises 20% of the total data, are the two components of the training data set.

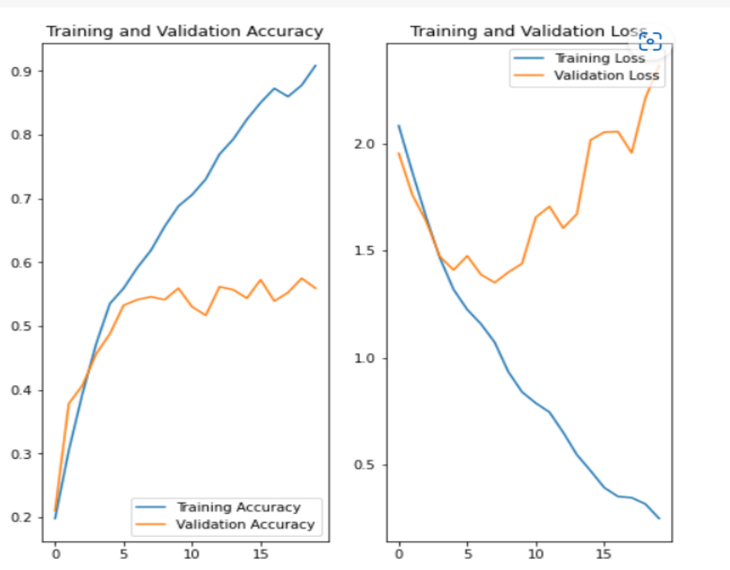

Figure-1

Since there is no skin cancer for the patient in question, Figure 1's validation accuracy and training accuracy differences are rather large, and the loss between the two graphs is also fairly large. This is the final graph that does not include data augmentation.
In the graphic below, the results of the data provided with data augmentation are displayed.

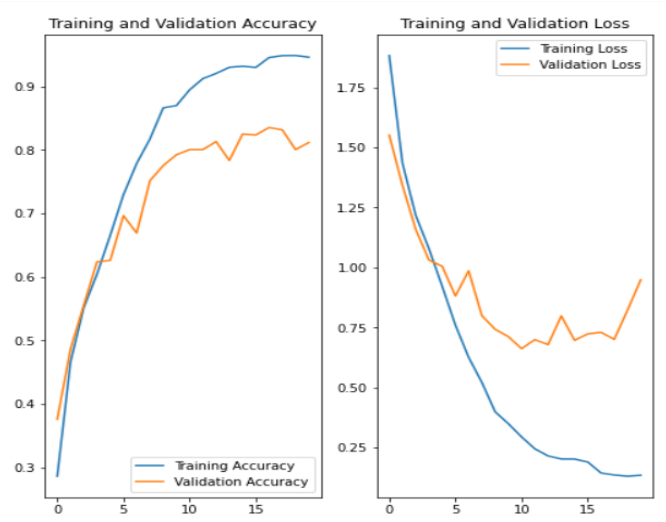

Figure-2

The difference between the figure-2 training and validation accuracy curves is less than it was in the preceding results. Training loss and validation loss don't really differ all that much. Given the outcome of this instance, it is now possible to make the medical diagnostic that the patient in issue has skin cancer.

In Table 1 analysis, we can see a performance comparison of each optimizer that is being used. This optimizer offers the best performance in terms of accuracy and loss. Values for precision, recall, and F1-Score fall between 0 and 1. The values of the performance parameters are near to 1, indicating that the CNN model will be able to classify a variety of skin cancers.

VI. CONCLUSION

Dermatologists would undoubtedly benefit from this skin cancer spotting method, which enables them to distinguish between different types of skin cancer quickly and effectively utilizing commonplace technology like cell phones and laptops. In this case, the procedure is applied using both the original data and the augmented data. The expanded dataset will produce a better outcome.

ACKNOWLEDGMENT

This work has been carried out at Department of CSE-AI ML at Malla Reddy Engineering College for Women (Autonomous), Secunderabad, India.

VII. REFERENCES

1. *Sara Medhat, Hala Abdel-Galil, Amal Elsayed, Hassan Saleh, Skin cancer diagnosis using convolutional neural networks for smartphone images: A comparative study, Journal of Radiation Research and Applied Sciences, Volume 15, Issue 1, 2022, Pages 262-267, ISSN 1687-8507,https://doi.org/10.1016/j.jrras.2022.03.008*
2. *Abbas Q, Emre Celebi M, Garcia IF, Ahmad W. Melanoma recognition framework based on the expert definition of ABCD for dermoscopic images. Skin Res Technol.2013 Feb;19(1):e93-102. doi: 10.1111/j.1600-0846.2012.00614.x.Epub 2012 Jun 7.PMID: 22672769.*
3. *Barata, Catarina &Ruela, Margarida & Francisco, Mariana & Marques, Jorge &Mendonça, Teresa. (2013). Two Systems for the Detection of Melanomas in Dermoscopy Images Using Texture and Color Features. IEEE Systems Journal. 8. 10.1109/JSYST.2013.2271540.*
4. *Hasan, Mahamudul& Barman, Surajit& Islam, Samia& Reza, Ahmed Wasif. (2019). Skin Cancer Detection Using Convolutional Neural Network. 254-258. 10.1145/3330482.3330525.*
5. *M. Ramachandra, T. Daniya and B. Saritha, "Skin Cancer Detection Using Machine Learning Algorithms," 2021 Innovations in Power and Advanced Computing Technologies (i-PACT), 2021, pp. 1-7, DOI: 10.1109/i-PACT52855.2021.9696874.*
6. *Pushpalatha, A & Dharani, P &Dharini, R &Gowsalya, J. (2021). Skin Cancer Classification Detection using CNN and SVM. Journal of Physics: Conference Series. 1916. 012148. 10.1088/1742-6596/1916/1/012148.*
7. *Brinker TJ, Hekler A, Utikal JS, Grabe N, Schadendorf D, Klode J, Berking C, Steeb T, Enk AH, von Kalle C. Skin Cancer Classification Using Convolutional Neural Networks: Systematic Review. J Med Internet Res. 2018 Oct 17;20(10):e11936. DOI: 10.2196/11936. PMID: 30333097; PMCID: PMC6231861*
8. *Mousannif, Hajar & Asri, Hiba & Mansoura, Mohamed &Mourahhib, Anas &Marmouchi, Mouad. (2021). Skin Cancer Prediction and Diagnosis Using Convolutional Neural Network (CNN) Deep Learning Algorithm. 10.1007/978-3-030-66840-2_42.*
9. *R. R. Subramanian, D. Achuth, P. S. Kumar, K. Naveen Kumar Reddy, S. Amara, and A. S. Chowdary, "Skin cancer classification using Convolutional neural networks," 2021 11th International Conference on Cloud Computing, Data Science & Engineering (Confluence),2021, pp.13-19, DOI: 10.1109/Confluence51648.2021.9377155.*