A CNN-Based Approach For The Detectıon Of Skın Cancer

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Abstract. Skin is the largest organ of the body. It frequently deals with a variety of problems indicating internal as well as external factors. Skin issues can be caused by pollutants in the environment, UV radiation, and poor skincare habits. There are many issues related to the skin like acne, sunburn, rosacea, and many more, and one of the major issues is skin cancer. Skin cancer is a type of cancer that originates in the cells of the skin. It can have significant effects on an individual's health and well-being. It starts as lesions on the skin when early detection is not done or timely medical attention is not taken then it leads to skin cancer. Melanoma, squamous cell carcinoma (SCC), and basal cell carcinoma (BCC) are the three primary varieties of skin cancer. This framework focuses on the detection of skin cancer at an early stage based on the skin imaging data and the dataset used in this paper is collected from Kaggle.com namely Melanomia. From the data, both spatial and sequential patterns are analyzed and also the features are extracted to forecast the occurrence of skin cancer. The dataset used for this paper comprises 3033 images with two different classes. A deep learning-based convolutional neural network is used to perform cancer prediction. Additionally, the activation functions SoftMax and Sigmoid and optimization techniques like Adam, RMSprop, and Nadam are applied to improve the model to make accurate predictions. CNN is used due to its ability to extract information from dermatological photos and also perform better classification by avoiding errors in the dataset. According to the analysis of the experiment results, CNN-RMSprop with a sigmoid activation function outperforms other CNN optimizers with 89.30% accuracy. Therefore, quick action would help minimize losses in skin disease, and the proposed work would be a significant step towards improving the lives of patients in the field of dermatology.

Keywords: Skin Disease, Skin Cancer, Convolutional Neural Network, Root Mean Square propagation, Squamous cell carcinoma (SCC), Basal cell carcinoma (BCC).

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1 Introduction

Skin lesion is a general term used in dermatology and medicine to describe any unwanted spot of the skin that differs from the surrounding tissue. A skin lesion is any irregularity on the skin's surface, such as discolorations, lumps, sores, pimples, or any other apparent change identified as a skin lesion. The two types of skin lesions are primary and secondary where primary skin lesions are abnormal skin conditions that can either be present from birth or develop over time. Primary skin lesions can become worse or change into secondary skin lesions [1]. The human skin is the largest organ in the body and can have a wide variety of lesions, such as benign moles, malignant tumors, and many types of dermatological disorders. Dermatology includes the identification, diagnosis, and medical treatment of a wide range of skin abnormalities and disorders, especially the detection of skin lesions. Dermatologists suggest three treatments for affected skin: home care, medications, or surgery, depending on the type of skin lesion [2]. Dermatologists make a lot of their diagnoses using traditional procedures, which can be lengthy and subjective due to visual inspection [3]. Machine learning is weak for the extraction of features, the preprocessing of the images is complex, and the accuracy is very low for the detection of skin diseases [4]. In recent years, Convolutional Neural Networks (CNNs) have certainly represented a major improvement in dermatology and medical imaging when it comes to the detection of skin lesions. An earlier predefined model was employed to identify skin lesion diseases; however, because of its incompatibility, the model's accuracy decreased and its predictions were inaccurate [5]. By using deep learning techniques, in particular, CNN, which is used for image classification, can identify diseases from skin images. This paper focuses on developing CNN for the classification of skin diseases and aims to produce accurate, mean, and cost-effective results for detecting the classification of the diseases that affect the skin. Convolutional Neural Networks (CNNs) are a cutting-edge method for addressing robustness and consistency problems in research, particularly in the context of skin lesion diagnosis [6].

2 Literature Survey

The studies in the literature on the identification of skin diseases can be broadly divided into two distinct categories. The first category involves using conventional machine learning techniques to analyze picture data for issues such as K-nearest neighbors (KNN), support vector machines (SVM), and decision trees (DT). The second group uses a deep learning technique with automatic feature extraction to classify outcomes based on the skin disease image dataset.

Noortaz et al. developed a procedure for skin disease detection using parallel CNN by using a skin cancer image dataset and got an overall accuracy of 79.45%. It only deals with 9 cases of skin cancer, and it gives an accuracy of 69.57% for VGG-16 and 71.19% for VGG-19 [7]. This literature survey is on two studies. The second study by Pomponiu et al. uses a pre-trained AlexNet for melanoma versus benign nevi classification with a focus on data augmentation and preprocessing, while the first study highlights the transferability of features learned from non-medical datasets, such as ImageNet, to the domain of skin lesions. It got an overall accuracy of 93.64% [8]. Maryam Naqvi et al. developed a procedure for skin cancer detection using deep learning by using a skin cancer image dataset and got an overall accuracy of 93.5%. It is involved in steps in computer-aided skin cancer diagnosis. In that, the essential steps are segmentation and classification [9]. Mohammed Ali Kadampur et al. developed a procedure for skin cancer detection by using DermIS and DermQuest datasets and got 97.6% accuracy for DermIS and 97.4% for DermQuest. It is focused on DL-based methods that use images for feature learning [10]. Yunendah Nur Fu'adah et al. developed a procedure for an automated skin cancer classification system for skin cancer by using the ISIC dataset and got an accuracy of 99% [11]. Rishu Garg et al. developed a procedure for skin cancer using CNN by using the MNIST HAM-10000 dataset and got an overall accuracy of 90.51%. In this paper, use the ResNet model [12]. Hardik Nahata et al. developed a procedure for skin cancer detection using deep learning using the ISIC dataset and got an accuracy of 91%. In this paper, use different optimizers, which are Inception V3, ResNet50, and VGG16. Finally, the InceptionResnet got better accuracy [13]. Karar Ali et al. developed a procedure for skin cancer by using the HAM10000 dataset and got an accuracy of 87.91%. In this, the EfficientNet B4 got the best accuracy [14]. Mohammed Monirujjaman Khan at el. developed a procedure for skin cancer using a Malignant dataset collected from Kaggle and got an accuracy of 93.18%. This journal uses different models, which are SVM, VGG16, and ResNet50. Finally, the VGG16 got the highest accuracy [15].

3 Material and Methods

3.1 Dataset

The melanoma dataset contains 2 types of skin diseases. There are around 10,000 images in our dataset out of which 3033 images had been split into training and test sets. The below diagram shows some diseases related to skin classes and the table show the information from the below classes.

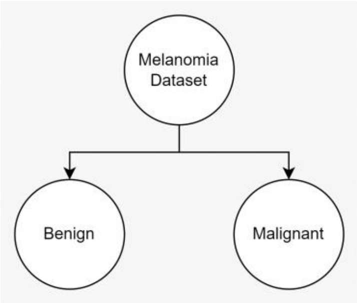


Fig.1. Skin cancer diseases

Benign Malignant

Fig.2. Sample images from skin cancer disease dataset

Table 1. An explanation of diseases that affect the skin

Class	No. of images in the dataset	Description
Benign	1683	Benign is a tumor that is a non-cancerous development and it does not spread to other parts of the body or infect any adjacent tissues. The benign tumors' cells are usually similar to normal cells and are usually confined.
Malignant	1350	Malignant is a growth of cells, that spreads to the nearby tissues and also to the other parts of the body through the circulatory system and is commonly referred to as cancer.

3.2 Proposed Methodology

The dataset for skin disease must first be loaded into the model. The collection consists of a variety of images connected to diseases, each with a label. Photos are resized and rescaled during the data preprocessing stage to improve efficiency.The next step is the division of the dataset into subsets for testing, training, and validation. Using images of skin taken over several epochs, a convolutional neural network architecture is trained in the second stage. The performance of the trained model is then evaluated using a variety of metrics, such as f-score, accuracy, precision, and recall. During the classification stage, the deep learning model identifies the disease in the image.

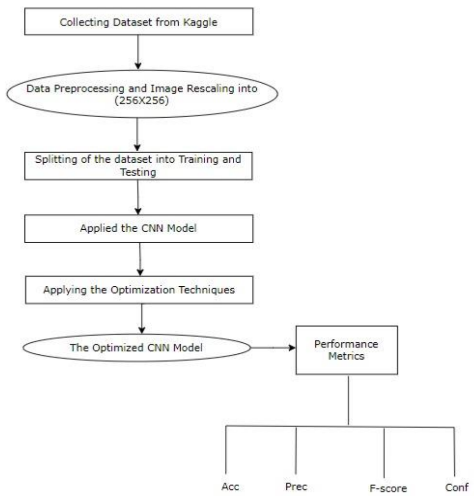


Fig.3. Overview of The Proposed Approach

The CNN architecture proposed by the proposed model consists of several layers: max-pooling, dropout, flattening, convolution with filters and rectified linear units (ReLU) activations, dense fully-connected, and output with a sigmoid activation function. Kernel sliding is used by the convolution layer to extract features from the input image. The pooling layer reduces the size of the data. A dropout layer is used to deactivate a portion of randomly selected nodes to prevent over-fitting. The flattened layer converts the multi-dimensional data into a one-dimensional array. In the end, the fully connected layer integrates the data, and the output layer classifies the data using a sigmoid function that enhances integration and yields high training and validation accuracy.

3.2.1 Convolutional Neural Networks

The concept of neural networks, especially Convolutional Neural Networks (CNNs) is a type of deep learning system that can be very useful for processing image and video data their concept originated from the human visual cortex. The ability of humans to extract features from picture data is impressive.

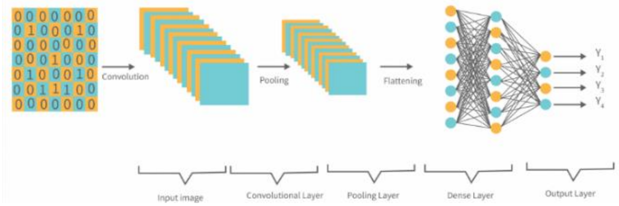


Fig.4. Overview of CNN architecture

3.2.1.1. Layers of convolution:

These layers move across the input image using tiny filters, or kernels. To identify particular elements like edges, textures, or shapes, the filter compares itself to various regions of the image. In doing so, feature maps capturing these identified features are produced.

3.2.1.2. Pooling layers:

By calculating the maximum or average value of a small neighborhood of pixels, these layers downsample the feature maps. This keeps important information while reducing the size of the data.

3.2.1.3. Fully interconnected layers:

These are similar to traditional neural network layers. They take the output of the pooling layers as input and use it to make predictions about the image, like its content, objects present, or even potential actions.

3.2.2. Function of Sigmoid Activation:

The Sigmoid Function curve appears to be in the shape of a S. It is commonly used in neural networks and machine learning. And it maps any real-valued number to a value between 0 and 1. It is specified for the models whose output is usually the prediction of probability. The sigmoid is the best option because probability only occurs in the interval between 0 and 1. It is well-suited for optimization algorithms used in the training of neural networks. It can determine the sigmoid curve's slope between any two points.

3.2.3. RMSprop optimizer:

RMSprop in short is written as Root Mean Square Propagation. It is an algorithm that is used for the optimization of the adaptive learning rate. It allows for faster convergence and better management of uneven landscapes in the optimization space by separately adjusting the learning rates for each parameter. It helps the model effectively learn from the data, adapt to different image characteristics, and converge efficiently during the training process.

3.2.4. Accuracy:

The simplest metric to determine the overall robustness of the model is accuracy.It calculates the proportion of accurately predicted cases to all instances.

$$Accuracy = \frac{TrueNegatives + TruePositive}{TruePositive + FalsePositive + TrueNegative + FalseNegative}$$

3.2.5. Precision:

Precision focuses on the right cases among the anticipated positive cases. It is defined as the ratio of all positive predictions to correctly predicted positive observations. When assessing the model's potential for false positives, accuracy plays a role.

$$Precision = \frac{TruePositive}{TruePositive + FalsePositive}$$

3.2.6. Recall:

The percentage of true positives (actual positives) that a model correctly identified is calculated using recall. Recall is best used when the cost of a false negative is significant.

$$Recall = \frac{TruePositive}{TruePositive + FalseNegative}$$

3.2.7. F1-score:

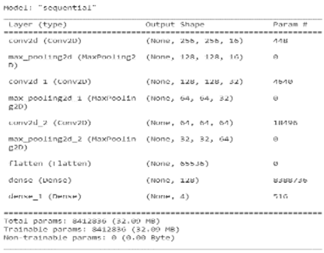
The precision and recall harmonic mean are represented by this. In terms of math, it looks like this:

$$F1 - Score = \frac{2*(Precision*Recall)}{Precision + Recall}$$

4 Experimental Results

The proposed CNN model was trained with a skin image dataset. The dataset is divided into three categories they are training, validation, and testing. The proposed model achieved 89.30% accuracy and 9.79% loss. Using activation functions such as Sigmoid and RMSprop optimizer gives the best accuracy for the classification.

4.1 CNN Model Summary



Model: "sequential"

Layer (type)	Output Shape	Param #
conv2d (Conv2D)	(None, 256, 256, 16)	448
max_pooling2d (MaxPooling2D)	(None, 128, 128, 16)	0
conv2d_1 (Conv2D)	(None, 128, 128, 32)	4640
max_pooling2d_1 (MaxPooling2D)	(None, 64, 64, 32)	0
conv2d_2 (Conv2D)	(None, 64, 64, 64)	18496
max_pooling2d_2 (MaxPooling2D)	(None, 32, 32, 64)	0
flatten (Flatten)	(None, 65536)	0
dense (Dense)	(None, 128)	8388736
dense_1 (Dense)	(None, 4)	516

Total params: 8412836 (32.09 MB)
Trainable params: 8412836 (32.09 MB)
Non-trainable params: 0 (0.00 Byte)

Fig.5. Proposed CNN Model Summary

4.2 Comparisons

Table 2. Comparison of Different Optimizers

Optimizer	Activation function	No. of epochs	Train Accuracy	Test accuracy
RMSprop	SoftMax	20	96.61 %	88.20 %
Adam	Sigmoid	20	97.15 %	88.90 %
RMSprop	Sigmoid	20	96.26%	89.30 %
Adam	SoftMax	20	99.56 %	89.40 %
Nadam	SoftMax	20	98.48 %	88.10 %

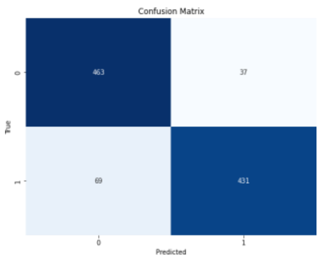


Fig.6. Adam

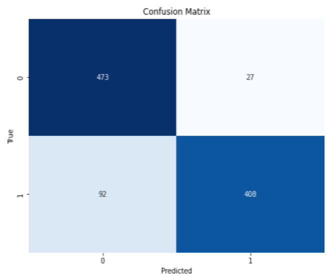


Fig.7. Nadam

4.3. Confusion Matrix:

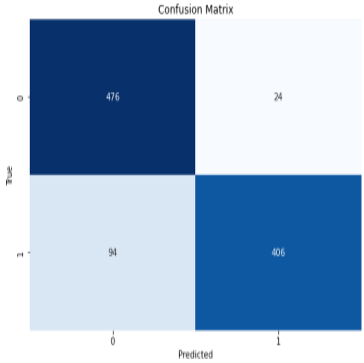


Fig.8. Confusion matrix of CNN model with RMSprop optimizer

The confusion matrix shows the predictions that are right and wrong with values in the above figure. The matrix's diagonal cells show the right predictions, while non-diagonal elements show the number of wrong predictions. In the above figure, the diagonal elements of the confusion matrix are [473,408]. These high values are necessary to support the suggested model's high effectiveness in classifying skin diseases. The trained model was able to classify every form of sickness with little difficulty. In melanoma diseases, the model identified 473 out of 500 cases accurately, only 27 instances were misclassified.

5 Conclusion and Future Scope

Deep learning algorithms, particularly Convolutional Neural Networks (CNNs), are trained on large datasets of images of skin lesions. The skin disease dataset consists of 3033 images that contain benign and malignant types of photos. It reviewed various methods of deep learning that are used to detect skin cancer and concentrated on applying deep learning algorithms to classify skin cancers. To compare CNN performance for disease classification, in this paper, CNN-Nadam, CNN-Adam, and CNN-RMSprop optimizers with fixed learning rates, epochs, and batch sizes on the skin cancer dataset were performed. The studies' results showed that CNN using the RMSprop had the best accuracy, at 88.20%. Additionally, CNN using the Adam optimizer scored 88.90%, and CNN using the Nadam optimizer scored 88.10% for accuracy. This research will be helpful in the future to get the best results.The future scope includes broadening the CNN-based disease classification system for skin cancer. And it is developing to be user-friendly for patients. However, it is an effective path toward the goal of delivering a more useful tool for doctors. This technology can save lives, improve patient outcomes, and revolutionize access to early diagnosis and appropriate treatment for everyone by addressing the issues. In this paper, use the RMSprop optimizer to get the best result. It allows for continuous monitoring of skin lesions and early detection of changes. And it provides accessible tools for timely decision-making and minimizing skin diseases.

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