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Skin Cancer Detection and Classification using Deep Learning Techniques

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Abstract

In recent years, one of the deadliest malignancies is skin cancer. If it is not detected and treated in a timely manner, it is expected to spread to other body parts. An accurate automated system for skin lesion recognition is essential for early detection to save human lives. Although there are many other forms of skin cancer, basal cell carcinoma (BCC), squamous cell carcinoma (SCC), and melanoma are the three most prevalent. With early identification and appropriate treatment, these three kinds of skin cancer can be successfully treated by using deep learning techniques. One of the main benefits of using deep learning for skin cancer detection is its ability to accurately classify images with subtle differences. In this paper, Image pre-processing is employed at an initial diagnosis for removing the artifacts present in the raw dataset and further Convolutional Neural Network (CNN) is employed to improve classification and detection of skin cancer with improved accuracy. For analyzing enormous volumes of data, R-CNN algorithms are proved to be incredibly effective in terms of accuracy of 84.32%. Due to its precision, effectiveness, objectivity, and accessibility, R-CNN algorithm have proven to be very helpful in the identification and categorization of skin cancer.

Keywords: Deep Learning; Image Processing; CNN; Transfer Learning; ResNet50

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1. Introduction

In the past, skin cancer has been the most common complaint worldwide. Cancer kinds that arise on the skin are known as skin cancers. The prevalence of skin cancer, both carcinoma and non-melanoma, has risen in recent years. One in five Americans will have skin cancer at some point in their lifetime, according to data from the skin Cancer Foundation. In the past, skin cancer has been the most common complaint worldwide. Cancer kinds that arise on the skin are known as skin cancers. The prevalence of skin cancer, both carcinoma and non-melanoma, has risen in recent years. One in five Americans will have skin cancer at some point in their lifetime, according to data from the skin Cancer Foundation. The World Health Organization (WHO) states that three out of every four instances of cancer can be connected to skin cancer. In nations like the US, Canada, and Australia, the number of cases of skin cancer has been rising over many centuries. It seems that skin disorders have a major negative impact on people's health worldwide. While people with different skin tones are about 20 to 30 percent less likely to contract melanoma than those with lighter skin, they have also been found to have a lower or advanced mortality threat for certain carcinoma types. Clinical evidence supports similar result differences with respect to race in cases of skin cancer. This is because abnormal cells are proliferating and may eventually invade on various bodily parts. Melanoma, squamous cell carcinoma (SCC), and basal cell carcinoma (BCC) are the three main types of skin cancer. The primary environmental element responsible for skin cancer is sun exposure-induced UV radiation. Age, light skin tone, smoking, HPV infections (which raise the risk of squamous-cell skin cancer), genetic disorders, chronic wounds that never heal, ionizing radiation from sources like X-rays, environmental carcinogens, and artificial UV radiation are additional risk factors that should be taken into account. Unnoticed skin cancer has the potential to take a person's life. Therefore, early detection of skin cancer cells is essential to preserve human life.

Computer vision systems have become increasingly popular in various research domains in recent years, including medical [1], leather inspection [2], error measurement [3], and so on. The diagnosis and detection of diseases in humans is greatly aided by learning algorithms and computer vision. Convolutional neural networks (CNNs) are learning techniques that have gained a lot of traction in recent computer vision applications. This is because CNNs are better at making predictions and tend to gravitate toward larger networks with more complex computational and memory requirements [4, 5]. Fig. 1 lists the common forms of skin cancer.

(a) Basal Cell Carcinoma (BCC) (b) Squamous-cell skin cancer (SSC) (c) Melanoma

Fig.1. Common types of Skin cancer

2. Literature Survey

This section contains a thorough assessment and analysis of academic journals and other information sources pertaining to the identification of skin cancer. The classification of skin cancer was based on the identification of only two types of cancer: malignant and benign. Many techniques were proposed with various Deep CNN (DCNNs) and Support Vector Machine (SVM) approaches, yielding good results.

Convolutional Neural Network (CNN) has recently gained prominence as a potent tool for skin cancer diagnosis. This study uses the Human Against Machine (HAM) 10000 dataset to illustrate the skin cancer classification method [6]. The dataset with 2437 training images, 660 test images and 200 validation images were used for the early cancer detection by utilizing deep learning architectures ResNet-101 and Inception-v3 [7]. This model could recognize seven different categories of skin lesions. On the HAM 10000 dataset, an analysis has been done for the classification and the transfer learning with multiple pre-trained models were used together with class-weighted loss and data augmentation techniques [8]. A Generative Adversarial Network (GAN) has been created to create fake images of skin cancer in order to make up for the lack of data needed to train the suggested CNN algorithm. Without the obtained synthetic images, the classification performance of the planned trained CNN was close to 53%, but by including the synthetic images in the primary database, the performance of the model was enhanced to 71% [9]. Deep neural network-based categorization techniques for computer-assisted skin cancer typically produce predictions based only on images of skin lesions. Although the results are encouraging, it is still feasible to improve the performance by taking into account patient demographics, which are significant indicators that human experts take into account when screening for skin lesions. The problem of applying deep learning models for skin cancer classification to combine image and metadata elements were discussed in [10]. The paper suggests an automated system for classifying skin cancer. In this classification, nine different forms of skin cancer were classified. Additionally, the effectiveness of deep convolutional neural networks (DCNN) was also observed. Nine different clinical kinds of skin cancer are included in the dataset, including actinic keratosis, basal cell carcinoma, benign keratosis, dermatofibroma, melanoma, nevus, seborrheic keratosis, squamous cell carcinoma, and vascular lesions [11]. Although melanoma, a type of skin illness, only accounts for a small portion of skin cancers in the USA, it accounts for more than 75% of all skin disorders linked to mortality in that country alone. One of the most effective methods for the early detection and treatment of skin cancer is skin lesion segmentation using machine learning. Recently, researchers segmented and diagnosed skin cancer using several deep network architectures [12]. Later, in 2020, hybrid detection techniques were proposed for detection of skin cancer using different deep learning architectures. The data collection of about 3000 images of people with skin conditions were collected for classification as malignant and benign. In this work, xception network provides highest classification with an accuracy of 85.303% [13].

In this proposed work, skin cancer is identified and classified into two categories as benign and malignant using image processing techniques and deep convolutional neural network (DCCN). The section 3 describes the proposed methodology where, the dataset used, pre-processing algorithms, data augmentation and deep learning algorithms are discussed. Followed by this, results and discussion has been done by using training and testing dataset. The comparison with the existing methods is also carried out in the section 4.

3. Proposed Methodology

In this work, we proposed a model capable of increasing performance significantly to classify seven types of skin cancer. The framework used in this method requires few GPU hours than a conventional search algorithm, which needs to train a model. A CNN is a particular type of network for deep learning algorithm which is utilized for tasks like image recognition, image classification and data processing. Although there are different kinds of neural networks in deep learning, CNNs are the preferred network architecture for identifying and recognizing objects. They are therefore ideally suited for computer vision (CV) applications where accurate object recognition is crucial, such as facial and self-driving automobile systems.

The architecture of CNN is made up of three layers namely Convolution layer, Pooling layer, and Fully connected layer. Pooling layer of the CNN is to extract the most salient features of the image while discarding the non-essential information. There are different types of pooling layers like max pooling, average pooling, L2-norm pooling etc. Max pooling is the widely used technique. It divides the input image into small rectangular blocks, and for each block it keeps only the maximum value. This reduces the size of each feature map without losing any important information, and it also helps to reduce overfitting. Overall, the pooling layer plays a critical role in reducing the dimensionality of the feature maps, providing translation invariance to the model and improving computational efficiency by reducing the number of parameters.

A network with three or more layers is a neural network, and deep learning is a subset of machine learning. Although far from being able to match the human brain's capacity for "learning" from vast volumes of data, these neural networks make an attempt to mimic its behaviour. Despite the fact that a neural network with a single layer can still produce approximations, more hidden layers can help to refine and optimize for accuracy.

Deep neural networks are made up of many layers of interconnected nodes, each of which improves upon the prediction or categorization made by the one underneath it. Forward propagation refers to the movement of calculations through the network. A deep neural network's visible layers are its input and output layers. The deep learning model ingests the data for processing in the input layer, and the final prediction or classification is performed in the output layer. Fig.2 shows the block diagram of the proposed method.

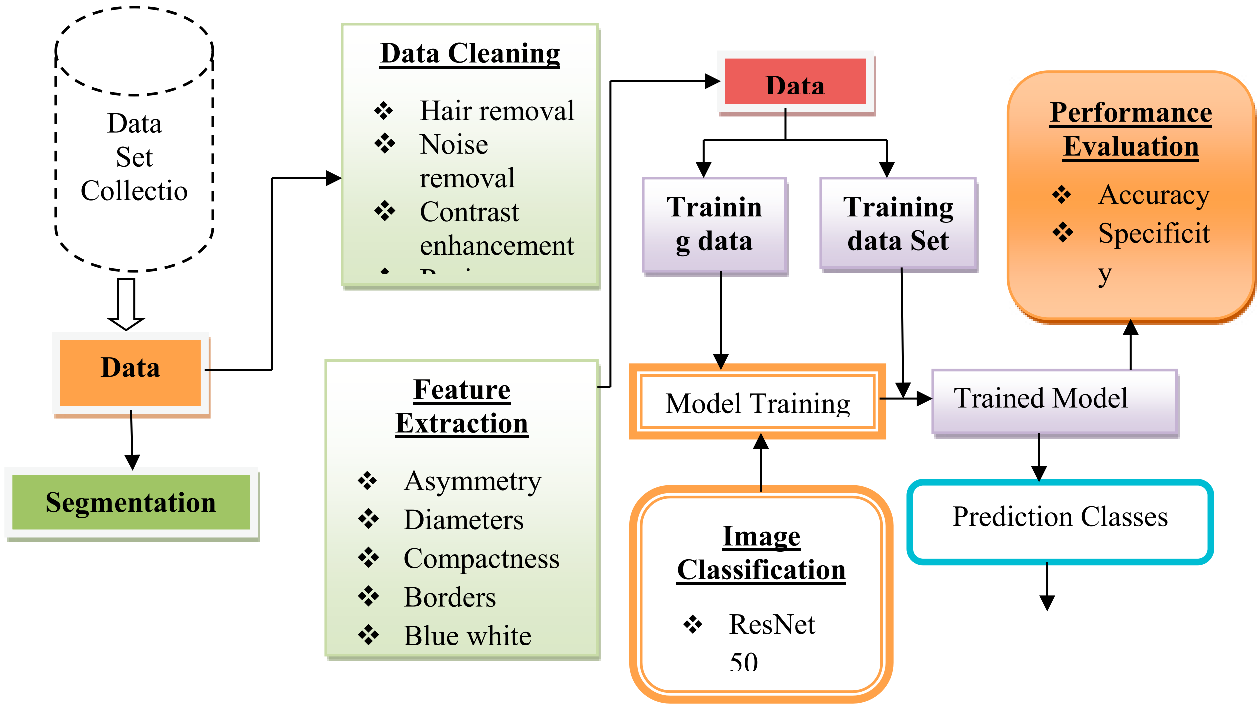


Fig.2. Flowchart of Proposed Model

3.1 Dataset

The International Skin Imaging Collaboration (ISIC) produced 2357 images of both malignant and benign oncological diseases for this collection. With the exception of melanomas and moles, whose photos have a minor predominance, all images were sorted according to the categorization determined with ISIC, and all subgroups were divided into the same number of images.

The data set contains the following diseases:

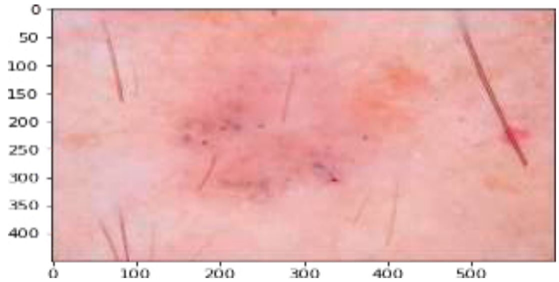
- Actinic keratosis
- Basal cell carcinoma
- Dermatofibroma
- Melanoma
- Nevus
- Pigmented benign keratosis
- Seborrheic keratosis
- Squamous cell carcinoma
- Vascular lesion

3.2 Pre-Processing

In order to eliminate noise and improve the quality of source image, pre-processing is a crucial stage in the detection process. The accuracy of the system can be significantly increased by carefully choosing the preprocessing approaches. It must be used in order to restrict the background image search for anomalies. The primary goal is to enhance the melanoma images quality by eliminating extraneous and irrelevant background elements and the resulting image will be used for further analysis.

The Segmentation is the process of breaking up the region of interest in an image. To accomplish this separation, treat each pixel in the image as having a similar attribute. The ability to handle images in segments as opposed to as a whole is the main advantage of segmentation. The segmented region of interest is depicted in Fig. 3. Segmentation is typically used to delineate the borders of a certain area.

Fig.3. Image Segmentation Skin Lesion



Data augmentation is the following stage of pre-processing. Data augmentation techniques are used in data analysis to increase the volume of data by creating new synthetic data from existing data or by appending copies of current data that have undergone significant modification. Fig. 4 provides some augmented images.

Fig.4. Data Augmentation Representation

3.3 *Feature selection and Finalization*

Extraction of relevant and distinctive features from the segmented lesion comes after the region of interest has been divided. Based on the ABCD rule, the lesion image has seven shape features and one colour feature derived from it. The four ABCD criterion (C) consists of two categories: chromatic information and the representation of shape characteristics (A, B, and D). Feature extraction is the most crucial stage in the model. Feature extraction is the process of extracting pertinent characteristics from the provided input dataset in order to carry out additional computations like detection and classification.

For further categorization purposes, features including the asymmetry index, diameter, standard vector, mean color channel values, energy, entropy, autocorrelation, correlation, homogeneity, and contrast are measured in order to aid in further classification. Energy, entropy, autocorrelation, correlation, homogeneity, and contrast are among the 14 properties that the co-occurrence matrix identifies. The best-fitting ellipse's major (D) and minor (d) axes are determined by its principal axes. Whether characteristics are chosen automatically or by hand rely on which features are most crucial for the prediction variable or intended result. The accuracy of the model may decrease if the model learns from features that aren't relevant to the data. By using a trained model object as a parameter, this function creates a model that has been trained using the whole dataset.

3.4 *Deep learning Algorithms*

Many artificial intelligence (AI) systems, which improve automation by doing mental as well as physical activities without human involvement, are based on deep learning. These models can be trained on a variety of data sources to improve their accuracy and robustness. Skin cancer diagnosis could become much more accurate and efficient with the use of deep learning, leading to earlier detection and improved patient outcomes. There are different deep learning algorithms available. In this work, the Convolution Neural Network (CNN) and Resnet50 Figures 5 and 6 illustrate the Model Architecture that was utilized for skin cancer detection and categorization. The CNN is the most recommended deep learning network architecture for identification and recognition. A deep learning Convolutional, pooling, and fully connected (FC) layers make up the three layers of CNN. The convolutional layer comes first, and the FC layer comes last. CNN becomes more intricate as it moves from the convolutional layer to the FC layer.

Convolutional Layer: The majority of computations happen in the convolutional layer, which is CNN's primary component. A convolutional layer that comes after the first one could be present. During the convolution process, a kernel or filter inside this layer travels over the receptive fields of the image to detect the presence or absence of features.

Pooling Layer: Like the convolutional layer, the pooling layer applies a kernel or filter to the input image. The pooling layer contains fewer input parameters than the convolutional layer, but it also results in some information loss. This layer makes the CNN more efficient and straightforward.

Fully Connected Layer: The CNN's FC layer categorizes images based on the attributes that were derived from the layers above. In this case, "fully connected" indicates that all of the inputs or nodes from the previous layer are connected to all of the activation units or nodes of the next layer.

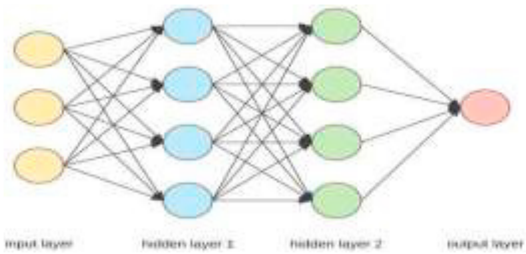


Fig.5. Flowchart of CNN Mechanism

ResNet50 consists of 50 layers, including convolutional, pooling, and fully connected layers. To extract features from the input images, a combination of 1x1, 3x3, and 5x5 convolutional filters are used. To improve the accuracy and efficiency of the network, batch normalization and ReLU activation functions come after the convolutional layers. In addition to its deep architecture and residual learning approach, ResNet50 also includes skip connections that enable it to learn more complex features from the input images. With these features, ResNet50 can make more accurate predictions about the content of images and achieve very high accuracy rates in image recognition tasks.

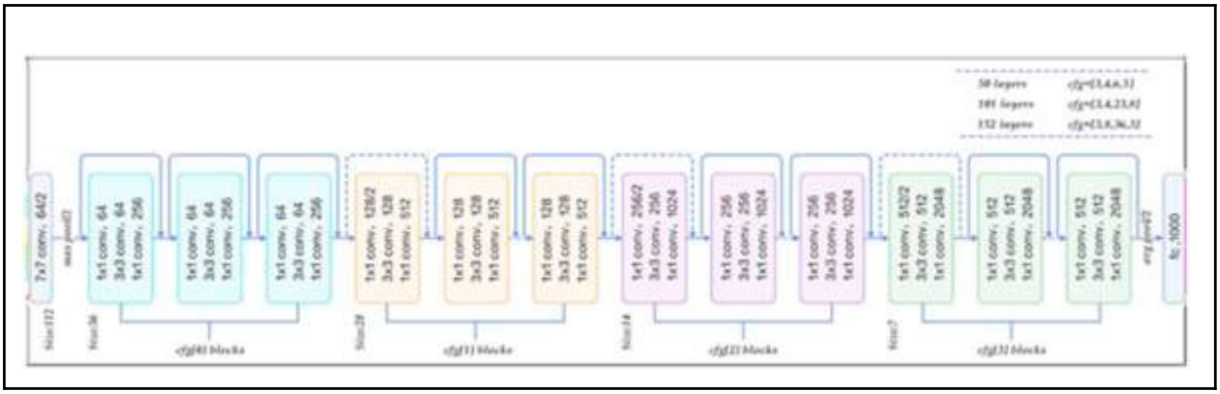


Fig.6. Block Diagrams of ResNet 50

4. Results and Discussions

The outcome of the model categorizes nine different forms of skin cancer and an overall bar graph representation is obtained and shown in Fig.7. Basal Cell Carcinoma, benign keratosis, vascular lesion, squamous cell carcinoma, melanoma, seborrheic keratosis, actinic keratosis, nevas are the types that were classified using this model. The accuracy is improved to 89.03% using this model. The execution time was much lesser than the other trained models. The count of skin cancer types using images has been represented below separately for each type of skin cancer.

Fig.7.Classification of skin cancer images

When predicting the probability of a specific outcome, the output of an algorithm that has been trained on a previous dataset is applied to new data. In earlier, diagnosis methods use huge amount of time to predict the type of skin cancer and its tumor cells, but using proposed model the type and count is easily predicted within a less amount of time with good efficiency and accuracy. Fig.8 shows the testing data for different types of skin cancer.

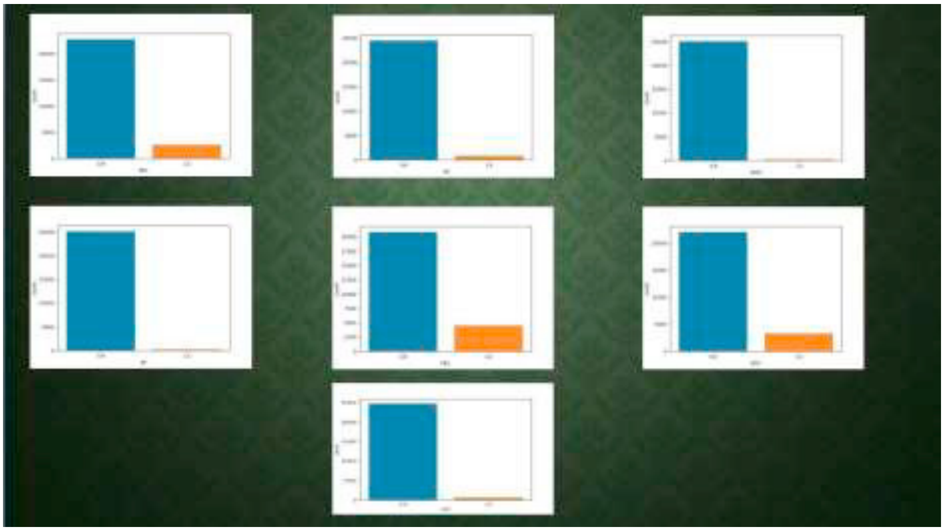


Fig.8. Different types of skin cancer images from the testing data

4.1 Confusion Matrix

An NxN table summarising the prediction performance of a classification model is constructed, where N is the number of classes. It is a correlation matrix that compares the model's categorization (predicted label) with the actual label. There are four categories into which the Confusion Matrices findings can be divided. When the model accurately predicts the positive class of an image, it is called a True Positive (TP). A False Positive (FP) is produced by the model when it forecasts an image's positive class inaccurately. When the model accurately predicts the negative class of an image, it is called a True Negative (TN). A False Negative (FN) occurs when the model fails to forecast the negative class. In a multiclass classification problem, the remaining labels are the negative class and the label for which the calculation is being done is the positive class.

4.2 Accuracy

The percentage of accurate predictions made using the test data is known as accuracy. It is readily determined by dividing the total number of forecasts by the number of correct predictions. The accuracy is increased to 89.03% using CNN deep learning model. The accuracy may be computed using a formula that contains True positive and False negative parameters. Fig. 9 displays the plot of accuracy, which is defined as the percentage of the total data that was properly predicted.

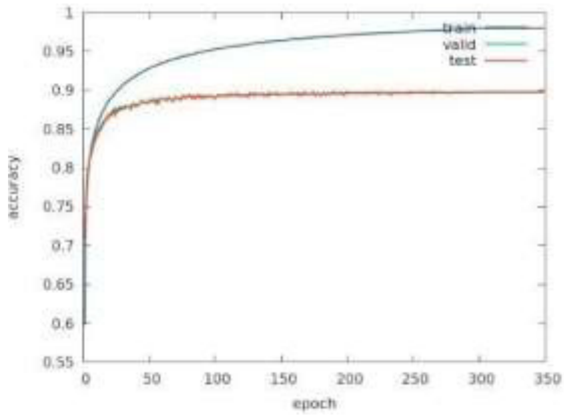


Fig.9. Accuracy Curve

Accuracy is the ratio of accurately predicted image classes to the total number of images. However, accuracy is only reliable in symmetric class distributions, or classes with approximately equal numbers of images or observations. We report Top-1, Top-2, and Top-3 categories of Accuracy for every EfficientNets B0-B7. Top-1 Accuracy is a traditional accuracy in which the class with the highest likelihood in the model's prediction matches the actual or expected class. Top-k Accuracy denotes the requirement that any of the model's top-k probability-based predictions match the image's actual class in order to be deemed accurate. The experiments used a publicly available dataset of melanoma photographs from the ISIC (International Skin Imaging Collaboration) database. The collection is limited to 640 images of skin lesions, including both benign and malignant lesions and was collected on several venues. They came from a device used for dermatoscopy. The remaining images will be used as a testing set, while the first 512 images will be used as a training set. CNN was trained with 124 x 124 images in three different methods. Ten epochs were used to train CNN. It has been demonstrated that the CNN works better than other two methods, despite the fact that traditional machine learning and image processing techniques have some advantages and can detect melanoma when a CNN cannot. In this case, a result aggregation of various methods is employed in order to improve the melanoma detection system's performance. In fact, rather than depending on a single model prediction, the fusion of many model predictions has systems. The training accuracy and training loss is validated and plotted in Fig.10 and Fig.11 respectively.

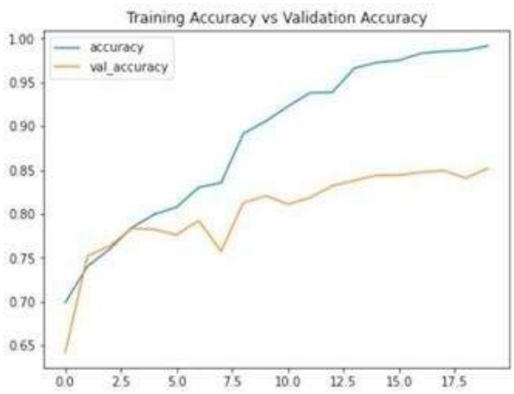


Fig.10. Training Accuracy Vs Validation Accuracy

Fig.11. Training loss Vs validation loss

Table.1. Comparison of Accuracy with the state of art datasets and the obtained accuracy

Study	Datasets	Number of classes	Best Classification Accuracy
[14]	11,444 dermoscopic images from the ISIC Dermoscopic Archive	5 classes	82.95%
[15]	HAM 10000 dataset	7 classes	87.91%
[16]	57,536 dermoscopic images from the ISIC Dermoscopic Archive	4 classes & Binary classes	89.3±1.1% & 94.5±0.9%
Proposed method	2357 images from ISIC database	9 classes	91.32%

The comparison of performance across the different datasets and the accuracy attained with the number of classes is shown in Table 1. Different clinical images in different combinations have been classified and divided into classes in this way. In the proposed method, an accuracy of 91.32% is attained for nine classes. When compared to our database, the other databases employ a greater number of images, which we accomplished in a shorter amount of time after completing the pre-processing phase.

5. Conclusion

This study proposed a unique CNN-based skin cancer detection technique. This method is able to efficiently capture skin cancer features through the use of parallel convolution blocks that has been thoroughly proved. The classification performance with CNN architecture is exceptional. The scheme of classification is exemplified by the nine types of skin cancer that were categorized in this study. Since it takes a lot of data to properly train and implement CNN-based architecture, we have used data augmentation techniques for the current dataset. The exploratory study demonstrates that the proposed method performs significantly better than the most advanced models, with increase in precision, recall, and F1 scores of 76.16%, 78.15%, and 76.92%, respectively. The weighted average and the overall accuracy of 91.32% are computed with the suggested model using a range of performance metrices. Ideally, the new research will address the cognitive difficulties in the future of detecting more cases of skin cancer and utilizing them to screen for skin cancers in AI-based systems, particularly in clinical practice.

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