iJRASET
International Journal For Research in
Applied Science and Engineering Technology

INTERNATIONAL JOURNAL FOR RESEARCH

IN APPLIED SCIENCE & ENGINEERING TECHNOLOGY

Volume: 12 **Issue:** IV **Month of publication:** April 2024

DOI: https://doi.org/10.22214/ijraset.2024.59725

International Journal for Research in Applied Science & Engineering Technology (IJRASET)
ISSN: 2321-9653; IC Value: 45.98; SJ Impact Factor: 7.538
Volume 12 Issue IV Apr 2024- Available at www.ijraset.com

Skin Cancer Detection

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Abstract: The skin is the largest organ and serves as a barrier to protect the internal organs, as well as the bones and muscles underneath it. When the skin deteriorates, the whole body is affected. Skin cancer is surprisingly common since the skin is so easily damaged by UV rays and other kinds of environmental pollutants. It seems that the two most common forms of skin cancer are benign melanoma and malignant melanoma. Malignant moles are significantly more harmful than benign moles and create bleeding blisters on the skin. They get their name because they resemble the more deadly melanocyte cells. Over 700,000 skin lesions are found annually in the United States, reports the American Cancer Society.

Apollo and other groups have shown that melanoma is more common in those above the age of 41. Current techniques allow for the possible early identification of skin cancer. Saving lives and preventing further spread of skin cancer depend on prompt diagnosis. People with lighter skin tones, regardless of age, are at a higher risk. It will be tough for even the most seasoned dermatologist to diagnose skin cancer and estimate how far it will develop. As a consequence, several applications and programs came into being. Every year, millions of people lose their lives to skin cancer, making it the most lethal form of the disease. In order to maintain a low mortality rate and a high survival rate, it is crucial to diagnose potentially dangerous cases of skin cancer early and treat them accordingly. Relevant publications mostly focus on the use of machine learning in algorithm design. However, the accuracy and precision provided by these algorithms are not always perfect. Image noise is reduced during preprocessing with the use of sharpening and smoothing filters. The optimal performance of the system was maintained, and new insights were gained, by using a deep learning convolution neural network (DL-CNN) for the multi-class classification of skin cancer. Indeed, all nine forms of skin cancer may be properly categorized using the study's findings.

I. INTRODUCTION

Skin cancer has been the most frequent cancer in the globe since the 1970s. In recent decades, there has been an increase in the diagnosis of both non-melanoma and melanoma skin cancers. While the World Health Organization (WHO) estimates that 1 in 3 people may get skin cancer at some point in their life, the Skin Cancer Foundation puts that figure at 1 in 5. In the Western Hemisphere, skin cancer has been on the increase for millennia. This trend is not exclusive to the US, Canada, or Australia; it can be seen in many other countries as well. The rapid spread and widespread impact of skin infections makes them a major public health concern. Skin cancer is responsible for 1.79 percent of the global disease burden in terms of disability-adjusted life years [1], according to a study published in 2017. Medicare in the United States lost more than $8 billion that year [2] because of the high expense of treating skin cancer, which accounts for around 7% of all newly diagnosed cancer cases worldwide. In spite of the fact that persons of color have a 20-30 fold increased chance of developing melanoma compared to those with lighter skin tones, the mortality risk has been shown to be either greater or lower depending on the kind of melanoma.

The key to effective treatment of a skin condition is a correct diagnosis. Cerebroscopy using this method may aid in the early detection of melanoma when it is easier to cure. Accurately diagnosing melanoma needs the skills of a dermatologist with relevant experience. Because malignant and non-malignant skin lesions seem identical and there is no clear demarcation between the two, melanoma may be difficult to identify. If a reliable automated method could be created to diagnose skin cancers by studying skin lesions, it would be a huge benefit to pathologists. In a time when information is becoming difficult to get, this is more crucial than ever. This study demonstrated the shortcomings of three popular categorization methods: K-nearest Neighbors, Support Vector Machines, and Decision Trees. After examining the mathematical underpinnings of classification, specialists concluded that deep learning models provided the most cutting-edge method of producing the desired outcomes. We tested out a broad array of mathematical models, some of which made use of learning algorithms and others of which did not. However, the quality and depth of activation were found to be insufficient in the pre-trained models. Together, we were able to combine our mathematical expertise and create a model called a Dense Convolutional Network, which has an accuracy of over 86.6%.

II. LITERATURE SURVEY

With the use of an ECOC support vector machine (SVM) and a deep convolutional neural network, Hameed et al. [3] developed a workaround. Using the proposed technique, pictures of skin lesions have been created, implemented, and assessed. It is now possible to label these images as either healthy, acne-prone, eczema-prone, benign, or malignant. There were 9,140 images from various sources included in the study. Alex NET, a pre-trained convolutional neural network model, was used to extract the features. For this specific classification task, we choose the ECOC SVM classifier. Accuracy improved to 86.21 percent with the help of ECOC SVM. A 10-fold cross-validation procedure was used to avoid overfitting the data. The results demonstrate that the retrieved characteristics from the convolutional neural network may help enhance the classification accuracy of a wide variety of skin lesions.

Aldhyani et al. [4] propose a CNN-based method that effectively employs kernels and activation functions. The proposed model used just 172,363 parameters but nevertheless managed an astonishing 97.85% accuracy on the test dataset. Data was segmented into seven classes for training the model. Disease classification may be aided by applying the proposed model on a dataset with additional categories. Benign keratosis, melanoma, and melanocytic nevi are all skin abnormalities that need to be worked on further before the model can consistently identify them.

Vakili et al. [5] describe a deep learning method to classify images of skin lesions such macules, nodules, papules, plaques, pustules, wheals, and bullas, with an eye on primary lesion classification and early-stage diagnosis. This framework employed deep learning techniques to categorize images of lesions into seven distinct groups. In this post, we experiment with several pre-trained deep convolutional neural networks to see which one produces the most accurate results. The results of the training and testing procedures showed that the ResNet-50 baseline model had improved to an acceptable 85.95% accuracy.

A state-of-the-art deep learning model for automatic multi-class classification of skin lesions was developed by Iqbal et al. [6]. Instead of using fewer filters and fewer parameters, the proposed Deep Convolutional Neural Network (DCNN) model takes use of additional layers and a more diverse range of filter sizes to improve efficiency and performance. Images acquired via dermoscopy are searched for in the ISIC-17, ISIC-18, and ISIC-19 databases maintained by the International Skin Imaging Collaboration. The aforementioned experimental results demonstrate the efficiency, reactivity, and specificity of the proposed DCNN approach. On the ISIC-17 accuracy scale, it scores 94%, while its sensitivity is 93%, and its specificity is 91%. The suggested DCNN method for skin lesion classification beats state-of-the-art algorithms, as shown by experimental findings, with an AUROC of 0.964 in the ISIC-17 dataset. This method may be utilized to assist dermatologists in this work. Considering the potential time, effort, and even human life savings that may follow from automating and speeding up the process of identifying skin lesions, the proposed technique is both novel and realistic.

Chaturvedi et al. [7] created a computer-aided diagnostic method for accurately classifying multi-class skin (MCS) cancers. The recommended strategy did better than both human professionals and the most effective deep learning algorithms when it came to identifying MCS tumors. Five pre-trained convolutional neural networks (CNNs) and four ensemble models were examined and improved upon using the HAM10000 dataset, with classification accuracy measured across seven classes. Our best single model had an accuracy of 93.20%, while our best ensemble model had an accuracy of 92.83%, according to this analysis. This framework recommends ResNeXt101 for MCS cancer classification because of its better design and greater accuracy.

Anjum et al. [8] proposed using convolutional neural networks (CNNs) for skin lesion detection. Important to the localization procedure is YOLOv2, which was created by layering ONNX with the Squeeze Net model. We conduct extensive tests to optimize the model's settings for precise lesion segmentation. The segmentation method achieves a Global Accuracy of 0.93 and 0.95 on ISBI 2017 and 2018, respectively. Classifying skin lesions using the ResNet-18 model and the cross entropy activation function. After collecting feature vectors, we utilize the ACO method to refine them. Classification accuracy was enhanced by the hybrid technique as compared to state-of-the-art methods.

An & et al. [9] proposed a transfer-learning strategy that makes use of an existing, trained Xception model. The original Xception model has one pooling layer, two thick layers, and a dropout layer added to it. After the previous FC layer was eliminated, seven skin disease categories were transferred to a new FC layer. The HAM10000 dataset was utilized to evaluate the proposed model because of its extreme skewness. Data augmentation techniques were used to complete the dataset and address the gaps in it. The latest results show that this model can accurately diagnose 96.40 percent of skin problems. When applied to the diagnosis of Benign Keratosis, the recommended model obtains a remarkable 99% accuracy, 97% sensitivity, and F1 score of 0.98. By reducing unnecessary anxiety and false alarms, this approach may provide patients and physicians a clearer picture of when medical intervention is required.

Srinivasu et al. [10] proposed using deep learning's Mobile Net V2 and Long Short-Term Memory (LSTM) to expedite the classification of skin diseases.

The Mobile Net V2 model is quick, precise, and resource-friendly. The proposed approach efficiently utilizes logs with refined data to provide trustworthy predictions. To monitor the transmission of disease, researchers use a co-occurrence matrix with shades of gray. Very Deep Convolutional Networks for Large-Scale Image Recognition (VGG) and an enlarged convolutional neural network architecture have also been used as performance benchmarks.

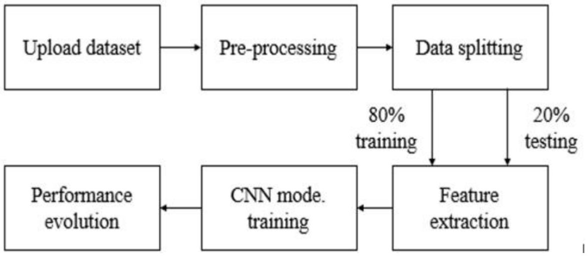
The article adopts a Convolutional Neural Network (CNN) constructed by Shanthi et al. [11], which is made up of numerous layers including the Convolution Layer, Activation Layer, Pooling Layer, Fully Connected Layer, and Soft-Max Classifier. Test cases from DermNet are used to evaluate the design. Acne, Keratosis, Eczema herpeticum, and Urticaria were the four main categories we pulled from the database, with 30-60 cases in each. Some of the challenges that must be overcome via automation include variations in skin tone, the location of sickness, and the need for specific equipment. The proposed CNN Classifier is accurate to within 0.04% of the actual classification rate.

Allugunti et al. [12] stated that a deep learning system may be able to effectively identify early melanoma subtypes. The three basic kinds of malignant lesions are identified in the proposed model: lesion malignant, superficial spreading, and nodular melanoma. This facilitates early diagnosis of the virus and the following isolation and treatment essential for eradicating it. Convolutional neural networks (CNNs) with deep layer topologies are used to demonstrate both DL and the more conventional non-parametric machine learning technique.

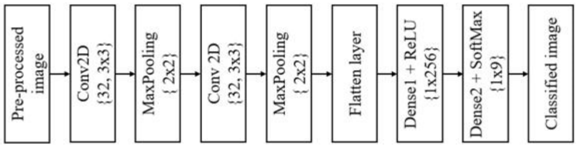
III. PROPOSED SYSTEM

Due to its recent rise in prominence in the area of image classification, CNN is used in this work to detect and categorize photos of skin disorders. The convolutional neural network was educated on data pertaining to a wide variety of skin lesions, such as actinic keratosis, basal cell carcinoma, dermatofibroma, melanoma, nevus, pigmented benign keratosis, squamous cell carcinoma, vascular lesion, and pigmented benign keratosis. Once trained, the CNN system can analyze any test picture and determine the disease shown. DL-CNN model-based CNN training:

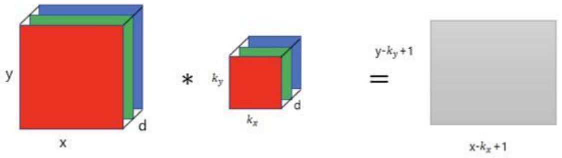
Convolution layers such as a kernel or filter, rectified linear unit (ReLU), max pooling, fully connected layer, and SoftMax layer with classification layer are used to transform input images into probabilistic values in the range [0,1] for object classification during training and testing of a deep neural network or when employing transfer learning.



The convolution layer provides the groundwork for extracting features from an input image by learning those characteristics in discrete pieces of training data. Source picture I(x, y, d) is a two-argument mathematical function, where "x" and "y" represent the image's row and column dimensions, respectively. F (k_x, k_y, d), where d is the size of the input image, may be represented as a filter or kernel with the same dimensions as the image.



Consider the case of a 5x5 input picture being processed by a 3x3 filter. Multiplying the values from the input picture by the filter's yields the feature map for the image.

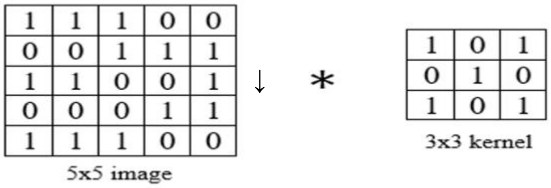


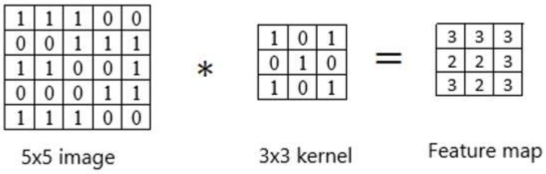
A. Max pooling Layer

Having this layer in place allows us to handle more complex images with fewer settings. Sub sampling (or down sampling) each feature map is a viable option to reduce their dimensionality without losing any informative detail. The largest feature in the current feature map is selected using the max pooling method.

B. ReLU Layer

Networks where the hidden layers are uncovered by means of a rectifier operation are known as rectified linear unit (ReLU) networks. If the input value is larger than zero, the ReLU function G() will return that number; otherwise, it will return zero. When max() is used over set 0 and the input x, the corresponding mathematical equation looks like this: G(x) = max{0,x}





IV. IMPLEMENTATION

A. Step-1 : Data Collection

The dataset is collected from Kaggle, a popular platform for hosting datasets and machine learning competitions. Users are prompted to select the directory containing the dataset using tkinter's filedialog.askdirectory() function.

```
filename = filedialog.askdirectory(initialdir = ".")
```

B. Step-2: Data Preprocessing

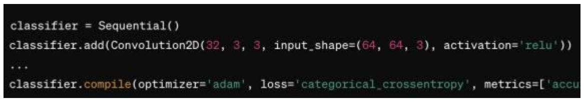
The dataset is loaded using NumPy's np.load() function. The dataset consists of input images stored in X and corresponding labels stored in Y.

The dataset undergoes preprocessing. After loading the dataset, it is revealed that it comprises 820 images. The data is further processed, including tasks such as normalization and shuffling, to ensure optimal performance during training and testing.

```
X = np.load('/Users/pineapple/Desktop/PROJECT PHASE/skin cancer code/model/X.txt.npy
Y = np.load('/Users/pineapple/Desktop/PROJECT PHASE/skin cancer code/model/Y.txt.npy
```

C. Step-3: Build CNN model

This step involves constructing the Convolutional Neural Network (CNN) model using Keras. The Sequential() function initializes the model, and various layers such as convolutional, max-pooling, flattening, and dense layers are added using the add() method.The model is then compiled with the Adam optimizer and categorical cross-entropy loss function.



```
classifier = Sequential()
classifier.add(Convolution2D(32, 3, 3, input_shape=(64, 64, 3), activation='relu'))
...
classifier.compile(optimizer='adam', loss='categorical_crossentropy', metrics=['accu
```

D. Step-4: Prediction

Users are prompted to select an image for disease prediction.

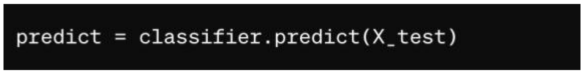
The selected image undergoes preprocessing and is fed into the trained CNN model for prediction.

```
predict = classifier.predict(X_test)
```

E. Step-5: Evaluation

The trained CNN model predicts disease labels for the test dataset. Evaluation metrics such as accuracy, precision, recall, F1-score, sensitivity, and specificity are calculated to assess the model's performance.

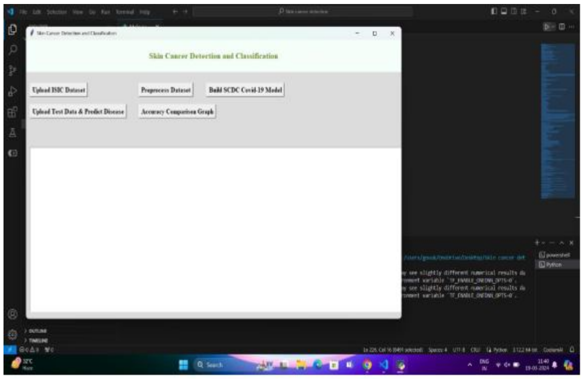
Additionally, a confusion matrix is generated to visualize the classification performance. Finally, an accuracy graph depicting the model's accuracy and loss over training epochs is plotted for analysis.

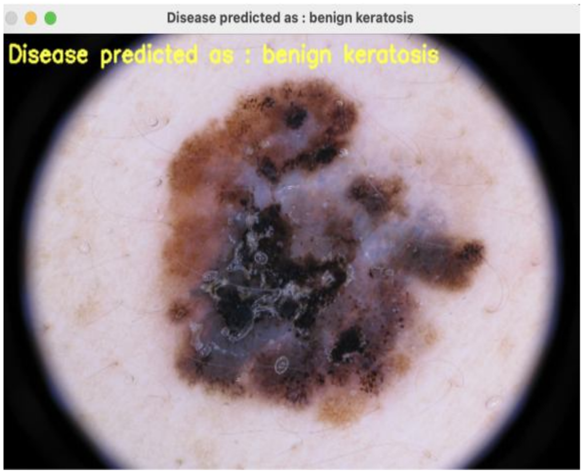


```
predict = classifier.predict(X_test)
```

V. RESULT AND ANALYSIS

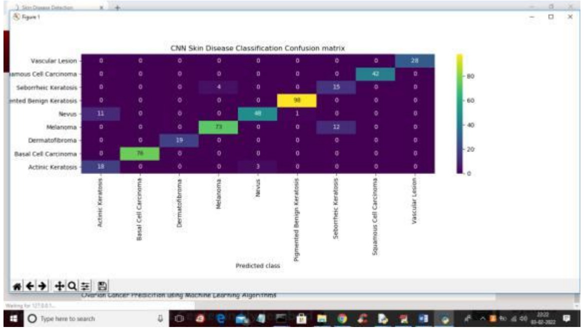
The code provides a user-friendly GUI interface for uploading, preprocessing, training, and testing a skin cancer detection and classification model using CNNs. It displays informative messages and results in a console-like textbox and allows users to interact with the system through buttons and file dialogs.





A. *Confusion Matrix*

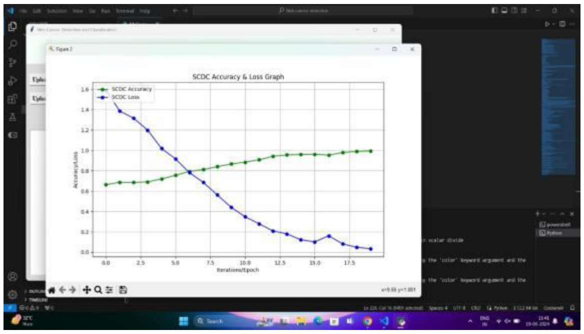
In the CNN confusion matrix graph above, predictions are made on test data. The x-axis represents the predicted disease names, while the y-axis represents the original test classes. The values in the diagonal boxes indicate correct predictions, where the predicted disease matches the actual disease class. Any values greater than 0 outside the diagonal represent incorrect predictions. Upon observation, it appears that only a few records are wrongly predicted. To further examine the performance and potentially identify areas for improvement, close the top graph to reveal any instances of decreased success rate in the CNN predictions.



	Actinic Keratosis	Basal Cell Carcinoma	Dermatofibroma	Melanoma	Nevus	Pigmented Benign Keratosis	Seborrheic Keratosis	Squamous Cell Carcinoma	Vascular Lesion
Vascular Lesion	0	0	0	0	0	0	0	0	28
amous Cell Carcinoma	0	0	0	0	0	0	0	42	0
Seborrheic Keratosis	0	0	0	4	0	0	15	0	0
nted Benign Keratosis	0	0	0	0	0	98	0	0	0
Nevus	11	0	0	0	48	1	0	0	0
Melanoma	0	0	0	73	0	0	12	0	0
Dermatofibroma	0	0	19	0	0	0	0	0	0
Basal Cell Carcinoma	0	76	0	0	0	0	0	0	0
Actinic Keratosis	18	0	0	0	3	0	0	0	0

B. *Accuracy And Loss Graph*

1) *X-Axis (Iterations/Epoch):* Represents the number of training iterations or epochs. Y-Axis (Accuracy/Loss):
2) *Accuracy:* Indicates the proportion of correctly classified instances out of the total instances.
3) *Loss:* Represents the error of the model's predictions compared to the ground truth labels.



VI. CONCLUSION

In this research, we aimed to develop the most effective possible deep learning convolutional neural network (DL-CNN) for the multi-class classification of skin cancer. Therefore, the study's results might be used for the precise classification of all nine types of skin cancer. Future work will refine this study so that reinforcement learning may be effectively employed to properly categorize skin lesions.

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