



SKIN CANCER DETECTION USING CONVOLUTIONAL NEURAL NETWORKS



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Abstract

The incidence rate of skin cancer is increasing day by day due to the increased exposure to the ultraviolet rays of sunlight. It is vital to detect skin cancer at an early stage in order to facilitate proper treatment and avoid any serious complications. For this work, we have designed a simple algorithm which detects if the skin image is suffering from any skin disease or not using deep learning algorithms. For this purpose, we utilized a CNN model based on TensorFlow which helps us in analyzing the images. All images are preprocessed before feeding them into the model. Color, shape and texture are some of the patterns learned by the model from the data set. Moreover, we have designed a web application through which users can upload images and get instant results. Cancerous or non-cancerous is the output of the system. The output obtained is reasonable enough for classification problems.

Introduction

Skin Cancer is among the most prevalent ailments suffered by individuals at present times. The condition arises because of an abnormal growth of skin cells after continuous exposure to ultraviolet rays. There are many skin cancer types, but melanoma is the most perilous since it metastasizes rapidly. Early diagnosis of skin cancer becomes vital in increasing survival rates. In conventional techniques, the manual skin examination process takes much time depending on expertise. In light of the above, there is a need for more efficient measures. As technology has evolved, deep learning models are becoming increasingly prevalent in image classification tasks. The Convolutional Neural Networks (CNNs) become particularly useful since they can learn features automatically from images.

In this work, a CNN classifier was designed to classify the skin image as cancerous or non-cancerous. Additionally, a very simple web interface was created to facilitate the usage of the classifier. The aim of this is to provide a very simple yet useful tool that could assist in early detection and help healthcare professionals. The objective of this is to develop an automated skin cancer detection system using the Convolutional Neural Network (CNN) model for classifying skin lesion images as cancerous or non-cancerous, enhance the performance of the model using data preprocessing and augmentation, measure the performance of the model using evaluation metrics like accuracy, precision, and recall, [1] provide real-time prediction using the web-based interface and reduce dependency on manual diagnosis and early detection.

Literature Survey

Several scientific studies are related to skin cancer detection via deep learning methods. Early works used convolutional neural networks (CNN) based on big datasets of skin images. The results of these studies allowed achieving a high level of accuracy and even surpassing dermatologists in some experiments. One of the techniques was based on ensemble methods using several CNNs in order to get better prediction accuracy. But this technique had a higher computation

complexity. Some researchers used publicly available datasets such as HAM10000 in order to get better results during training. They showed that good performance greatly depends on quality and balance of dataset. Nowadays there are many researches which use transfer learning and use pre-trained models such as ResNet and DenseNet. Such approach allows to decrease training time and improve the model performance but requires additional tuning. Based on the above literature review it can be stated that CNN models are appropriate for skin cancer detection. There are some problems with big and balanced datasets and computational complexity. Our goal is to create simple and efficient algorithm with good accuracy.

Author(s)Name	Year	Technique Used	Remarks
Esteva et al.[2]	2017	Deep CNN trained on a Large dataset of dermoscopic images	Demonstrated dermatologist-level classification performance using deep learning. Requires very large labelled dataset and high computational power
Codella et al.[3]	2018	Ensemble of CNN Models for skin lesion classification	Complex architecture increases computational cost. Improved classification accuracy using ensemble learning techniques
Tschandl et al.[4]	2019	CNN-based classification using HAM10000 dataset	Performance depends heavily on dataset quality and class Balance. Highlighted the Importance of large, well-annotated datasets for reliable predictions
Brinker et al.[5]	2019	Deep learning model Compared with Dermatologists	Limited generalization across different Datasets. Showed AI models can match or exceed dermatologist-level accuracy in specific condition
Mahbod et al.[6]	2020	Transfer learning using pretrained CNN Models (ResNet, DenseNet)	Requires fine-tuning and careful hyperparameter selection. Achieved improved performance with reduced training time using transfer learning
Almarazamian et al.[7]	2021	CNN-based automated Skin lesion classification	Limited performance on rare classes and imbalanced datasets. Demonstrated effectiveness of CNNs for automated skin cancer detection

Proposed Methodology

This system is used to detect the skin cancer using CNN algorithms. The system is designed to classify skin images into cancerous and non-cancerous categories using a CNN model.

Step-by-step process:

Step 1: Create a Python project.

Step 2: Collect dataset (CSV format) and abusive word dictionaries (offensive, explicit).

Step 3: Import required libraries such as transformers, re, sklearn, pandas, and rapidfuzz.

Step 4: Read input (text/audio/video/URL/dataset) and perform preprocessing:

Convert text to lowercase

Remove punctuation

Normalize obfuscated words

Step 5: Tokenize the input text into words.

$T = \text{Tokenizer}(D)$

Step 6: Load offensive and explicit word dictionaries.

Step 7: Detect abusive words using dictionary matching:

$$W_m = \{w \in T \mid w \in Dict\}$$

Step 8: Predict unseen abusive words using similarity matching:

$$W_p = \{w \mid \text{similarity}(w, w_d) \geq \theta\}$$

Step 9: Load pre-trained transformer model (Toxic-BERT) and classify text:

$$L, S_m = \text{Model}(D)$$

Where

L= Label (toxic / neutral)

S_m= Model confidence score

Step 10: Calculate severity score based on detected words:

$$S_v = \sum w_i$$

Where:

Explicit word → 3

Offensive word → 2

Step 11: Normalize severity and compute confidence:

$$S = \min(5, S_v)$$

$$C = \frac{S_v}{5}$$

Step 12: For audio/video/URL input:

Convert speech to text

Apply same pipeline

Step 13: For dataset input:

Predict labels for all records

Compute evaluation metrics:

$$\text{Accuracy} = \frac{TP + TN}{\text{Total}}$$

$$\text{Precision} = \frac{TP}{TP + FP}$$

$$\text{Recall} = \frac{TP}{TP + FN}$$

$$F1 = \frac{2PR}{P + R}$$

Step 14: Generate final output: $O = \{L, S, C, W_m, W_p\}$

Step 15: Return the result and store in log file

3.1 System Architecture

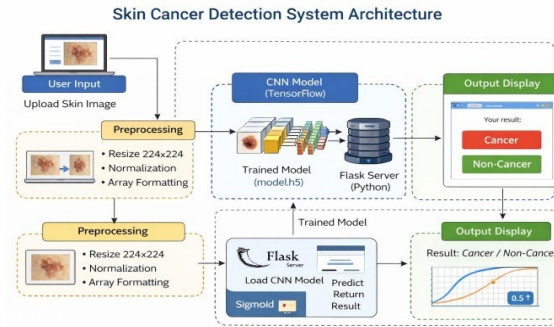


Fig1: System Architecture

There is a process that takes place. Firstly, the user will upload the image using the web interface. Then, the image will be processed and fed to the CNN model. In the end, the output will be displayed.

Data Collection: The data set that is used contains images of skin lesions, which are categorized as follows: Cancerous and non-cancerous. These images are classified in folders for convenience during training.

Data Preprocessing: Before training, the images undergo preprocessing: Resizing images to 224×224 pixels, converting images into arrays, normalizing pixel values between 0 and 1. This step helps improve model accuracy and stability.

CNN Model Architecture: It includes Convolution layers for extracting features, ReLU activation function, Max pooling layers, Fully connected layers and Sigmoid output layer.

Model Training: The model is trained using Batch size: 32, Epochs: 5 and Training-validation split: 80:20.

Model Deployment: After training, the model is saved and integrated into a Flask backend.

Prediction: The system processes user input and classifies it:

Output > 0.5 → Cancerous,
Else → Non-cancerous

Results & Discussion

Testing of the developed model was done by giving various inputs in the model, and this will enable one to assess the efficiency of the developed model. The model proved to be successful in predicting images with high accuracy levels. The accuracy of the training model is around 90-95% while the validation accuracy is around 85-90%. This means that the model is learning efficiently and has the capacity to generalize on unseen data. By looking at the accuracy graph, one can see that as the number of epochs increases, the performance of the model improves gradually. The value of loss decreases meaning[8] that the error rate is reduced. Model was also tested by using the web-based interface where users were able to upload images and get the results quickly from the model. The advantages of the developed system are quick detection, usability, and prediction of results instantly. Some of the disadvantages of the developed system include binary classification, usage of small data sets, and fast prediction. In conclusion, the findings show that the system functions well in the sense of easy implementation. However, the model can still be improved with other efficient methods.

In this work, the CNN model has been employed to recognize the type of skin image which could be cancerous or non-cancerous. The structure of the CNN model has been designed in a way that it can detect the features without extracting the features manually. The process of how the CNN model works can be described step by step. First of all, input images are subjected to convolution layers that filter different areas of the images and extract certain features like edges, textures, and other color information. It is due to the reason that the skin cancer images have unique patterns and shapes. Then, the activation function is used, ReLU in our case. The reason why it is done is that this activation function introduces the non-linearity into the network that allows learning complicated relations in the data. Without it, the whole CNN model would be a [9] simple linear model and could not work effectively with image classification. The last step of the model is applying pooling layers that reduce the size of feature maps and decrease the computational power and help with overfitting problem. Max-pooling is being used in our case. This flattened output is then fed to the fully connected layers. The fully connected layers behave as a kind of decision-making component of the neural network, where the feature vectors extracted will be classified into either class. Lastly, the sigmoid activation function will be applied on the output layer, as this is a binary classification problem. This function produces an output of values from 0 to 1, which determines the possibility of the image being cancerous.

Confusion Matrix Analysis

As shown in the confusion matrix, the model is able to correctly classify most of the images.

- True Positives → correctly identified cancer cases
- True Negatives → correctly identified non-cancer cases
- False Positives → normal image predicted as cancer
- False Negatives → cancer image predicted as normal

With respect to medicine, the problem with false negatives is more important since missing one case of cancer is potentially fatal. Therefore, improving this area is essential in future research.

		Predicted	
		Spam	Non-spam
Actual	Spam	600 (True positive)	300 (False negative)
	Non-spam	100 (False positive)	9000 (True negative)

Fig 2- Confusion matrix showing classification performance of the model.

Mathematical Representation (Explained Simply) The convolution operation can be written as: Feature Map = Input $\times$ Kernel + Bias

This means the model applies a small filter (kernel) on different parts of the image to extract features.

The ReLU activation function is given by:

$$f(x) = \max(0, x)$$

This function simply removes negative values and keeps positive values, which helps the model learn faster.

The sigmoid function is used for final classification: $\sigma(x) = 1 / (1 + e^{-x})$

This converts the output into a probability value between 0 and 1.

The loss function used is Binary Cross-Entropy: Loss = $-[y \log(p) + (1 - y) \log(1 - p)]$

Where:

- y = actual value
- p = predicted value

This function measures how far the prediction is from the actual result.

Conclusion & Future Work

This work shows the potential of AI in healthcare and its ability to support early detection. For this, we have created an automated deep learning model to detect skin cancers. The model is designed to classify images of the skin and provide output via a web interface. Although the model performs well, there is scope for improvement. In the future, we can use larger datasets, apply transfer learning, extend to multi-class classification and develop a mobile application

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