Skin Cancer Classification Using CNN

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Abstract

Skin cancer is one of the most dangerous forms of cancer, particularly when not detected early. Without timely diagnosis and treatment, it can spread to other parts of the body, making it more difficult to treat. Early detection plays a critical role in saving lives, and as such, an automated system for skin lesion recognition is highly valuable. This system not only saves time and effort but also aids in reducing the burden on healthcare professionals. The integration of image processing techniques with deep learning, particularly through Convolutional Neural Networks (CNNs), provides an efficient solution for the detection and classification of skin cancer.

This paper focuses on using CNNs to classify skin cancer into four types, as well as differentiate between cancerous and healthy skin. By leveraging CNNs, the system processes skin images to accurately identify various conditions, including melanoma, squamous cell carcinoma, nevus pigmentosus, and dermatofibroma. The deep learning model demonstrates a high classification accuracy of 94%, outperforming traditional machine learning approaches. The model is designed with multiple convolutional layers, max-pooling, and batch normalization, followed by fully connected layers and a SoftMax output for classification. Additionally, Adam optimizers have been evaluated to improve performance. This approach not only improves diagnostic efficiency but also has the potential to enhance treatment outcomes by enabling timely intervention.

Keywords: Adam optimizer, TensorFlow, CV2, Feature Extraction, CNN

1. INTRODUCTION

Skin cancer is one of the most common types of cancer globally, with melanoma being the deadliest form. Early detection is crucial for effective treatment, as it significantly improves survival rates [5], [10]. Diagnosing skin cancer remains a challenge due to the subtle differences between benign and malignant lesions, and traditional methods, such as visual inspections and biopsies, are time-consuming and require a high level of expertise [1], [4]. Furthermore, the growing demand for dermatological services, coupled with a shortage of trained professionals, has exacerbated the issue, particularly in underserved areas [3].

Recent advancements in artificial intelligence (AI), particularly deep learning, have demonstrated promise in automating detection processes. Convolutional Neural Networks (CNNs) have shown significant success in image recognition tasks, including medical image analysis, as they can automatically learn complex features from images [2], [9]. These advancements make CNNs ideal for detecting skin cancer from dermoscopic images, where early signs such as melanoma are visible [8], [7]. This project explores the use of CNNs to classify skin lesions and automate skin cancer detection. By leveraging a deep learning-based approach, it aims to aid dermatologists in making quicker, more accurate diagnoses and to provide a scalable solution for early detection, particularly in resource-constrained settings [6]. The system classifies skin lesions into categories such as melanoma, squamous cell carcinoma, dermatofibroma, and nevus pigmentosus, using dermoscopic images for analysis [10]. In addition to aiding healthcare professionals, the project includes an easy to-use interface that allows patients to upload images of their skin lesions 1 and receive immediate feedback, encouraging timely medical attention when necessary [5]. By addressing limitations in current diagnostic methods, this project aims to enhance the accessibility, speed, and reliability of skin cancer detection, contributing to better patient outcomes and reducing mortality rates associated with the disease [4].

2. Literature Review

The utilization of Convolutional Neural Networks (CNNs) for the identification of skin cancer has been extensively studied. Various research works have explored different techniques and models to enhance the accuracy and reliability of skin cancer classification.

Vidya M and Dr. Maya V Karki (2020) presented a machine learning-based approach for detecting skin cancer. Their methodology involved pre-processing techniques to enhance lesion visibility, segmentation using geodesic active contours (GAC), and feature extraction using the ABCD method. Classification was performed using SVM, KNN, and Naïve Bayes, showing promise in improving image quality and lesion focus. However, the study was limited by a small dataset of only 1000 images, restricting its generalizability.

Mohd Anas, Ram Kailash Gupta, and Dr. Shafeeq Ahmad (2017) focused on a non-invasive method utilizing K-means clustering for segmentation and color-texture feature extraction. Classification was performed using Support Vector Classifier (SVC) and Nearest Neighbor algorithms, reducing the need for biopsies. However, the accuracy was highly dependent on input image quality, particularly clarity and contrast.

Vigneswaran Narayana Murthy and P. Padmapriya (2018) investigated non-invasive techniques such as optical methods, sonography, electrical bio-impedance, and thermal imaging. These methods provided high-resolution lesion visualization, reducing the need for invasive diagnostics. However, their effectiveness was sensitive to noise, requiring advanced and sometimes costly equipment.

Shalu and Aman Kamboj (2018) proposed a color-based approach for melanoma detection, comparing Naïve Bayes, Decision Tree, and K-Nearest Neighbors classifiers. The Decision Tree classifier achieved an accuracy of 82.35%. However, the method's reliance on color features limited its ability to capture texture and shape characteristics, affecting its accuracy for some skin cancer types.

Arthur A. M. Teodoro, Douglas H. Silva, and Renata L. Rosa (2022) explored a skin cancer classification approach using Generative Adversarial Networks (GANs) and Region of Interest (ROI)-based attention mechanisms. Their method incorporated U-Net for segmentation and Efficient Attention Net for classification, significantly improving accuracy. However, performance depended heavily on dataset quality and diversity.

R. Zhang [7] proposed a melanoma detection model leveraging EfficientNet-B6 for fine-grained analysis of skin lesion images. Evaluations on the ISIC 2020 Challenge Dataset demonstrated state-of-the-art classification performance compared to previous melanoma classifiers.

S. Aswath and M. Kalaiyarivu Cholan [8] developed a method for identifying various skin diseases using feature extraction techniques such as color histogram, HOG, LBP, and gray-level co-occurrence matrix. They employed classifiers including Random Forest, XGBoost, SVM, and CatBoost, achieving enhanced classification accuracy. Additionally, an improved Xception model was utilized for optimal results.

A study [9] performed experiments on a dataset containing 4000 skin cancer images, with 1000 images per class. Using AlexNet, the model effectively classified test data, indicating promise for early skin cancer detection.

Pradhumn Agrahari, Archit Agrawal, and N. Subhashini [10] introduced a multi-class skin cancer detection method using a pre-trained MobileNet model on the HAM10000 ISIC dataset. Their approach demonstrated dermatologist-level performance, facilitating potential clinical advancements in healthcare practices.

A CNN deep learning algorithm was also assessed for its ability to categorize normal and cancerous moles [12]. Using the ISIC dataset with 2460 colored images, the model was built with Keras and TensorFlow. By optimizing parameters and classification functions, the proposed VGG-16 model achieved an accuracy of 87.6%.

3. Methodology

3.1 Dataset

The ISIC (International Skin Imaging Collaboration) Dataset is a widely used public dataset for the development of automated skin cancer classification systems. It contains high-quality dermoscopic images of both benign and malignant skin lesions, annotated by expert dermatologists. This dataset serves as a benchmark for training and evaluating deep learning models for skin cancer classification.

The dataset includes images categorized into five distinct classes:

1. Melanoma
2. Dermatofibroma
3. Nevus Pigmentosus
4. Squamous Cell Carcinoma (SCC)
5. Healthy Skin

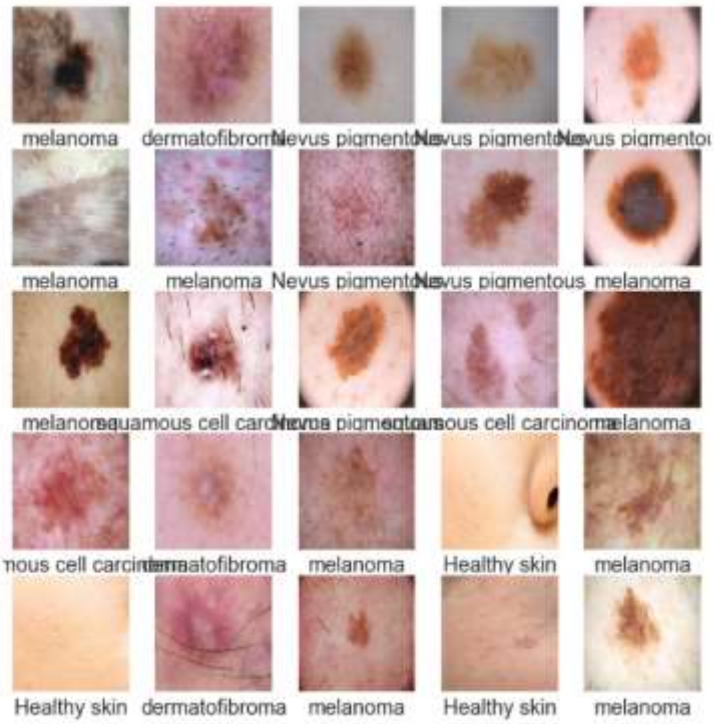

Figure 1: Sample Images of Skin Cancer

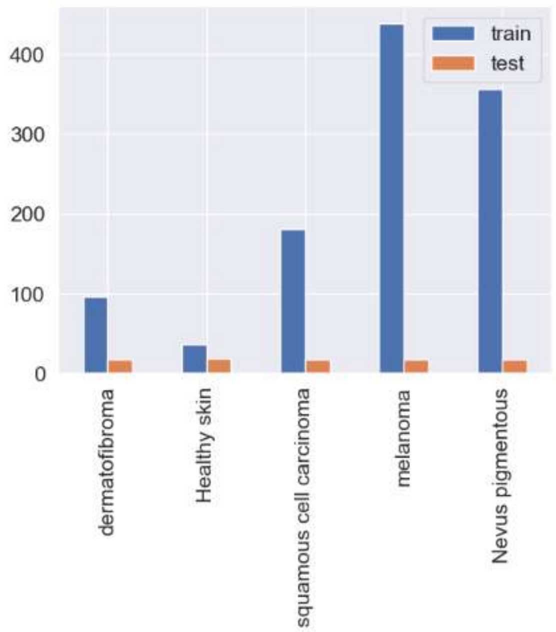

Figure 2: Dataset Distribution Across Classes

3.2 System Design

Figure 3 state the design of our model describing the flow of our system working from convolutional layers and pooling till the layers which are fully connected and then classification.

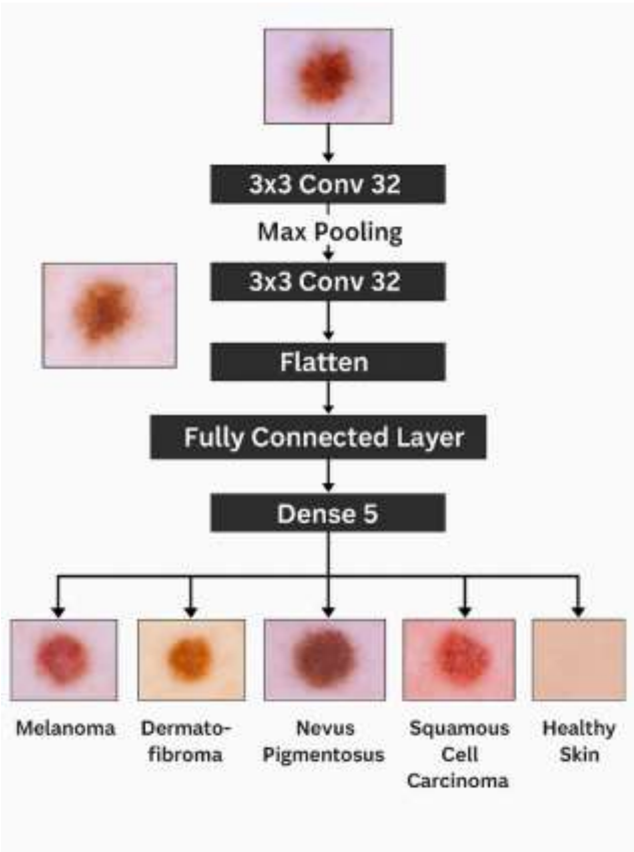

Figure 3: System Design

3.3 Algorithms

Skin cancer detection using CNN (Convolutional Neural Networks) has been an active area of research in recent years. This methodology is used for image classification and have shown promising results in detecting skin cancer.

Convolutional Neural Networks (CNN): CNN have been widely utilized for skin cancer identification and classification due to their ability to automatically extract relevant features from medical images. A CNN typically consists of convolutional layers, pooling layers, and fully connected layers, which work together to analyze and classify skin lesions based on learned patterns.

In this project, a CNN model was designed and trained to classify skin lesions into five categories: Melanoma, Dermatofibroma, Nevus Pigmentosus, Squamous Cell Carcinoma, and Healthy Skin. The model processes input dermoscopic images and extracts features through a series of convolutional and pooling layers, reducing spatial dimensions while preserving crucial information. The extracted feature maps are then flattened and passed through fully connected layers to perform the final classification.

A well-structured CNN architecture enables effective pattern recognition, improving the model's ability to differentiate between various skin cancer types. The integration of deep learning techniques into medical diagnostics enhances the accuracy, efficiency, and reliability of skin cancer detection, aiding healthcare professionals in early diagnosis and treatment planning.

2) Adam: To fine-tune the learning process and improve model performance, the Adam optimizer was employed in this project. Adam is an adaptive optimization technique that dynamically adjusts the learning rates of individual model parameters, allowing faster and more stable convergence during training. By computing first and second-moment estimates of gradients, Adam enhances the learning process and ensures efficient weight updates, leading to improved classification accuracy.

The use of Adam in this skin cancer detection model contributes to better generalization, reduced training time, and higher classification accuracy, making it a robust choice for optimizing deep learning models in medical image analysis.

3.4 Model Summary

Layer (type)	Output Shape	Param #
conv2d (Conv2D)	(None, 148, 148, 32)	896
max_pooling2d (MaxPooling2D)	(None, 74, 74, 32)	0
conv2d_1 (Conv2D)	(None, 72, 72, 32)	9,248
max_pooling2d_1 (MaxPooling2D)	(None, 36, 36, 32)	0
flatten (Flatten)	(None, 41472)	0
dense (Dense)	(None, 128)	5,308,544
dense_1 (Dense)	(None, 5)	645

Figure 4: Model Summary

The output from the summary() method is displayed in Figure 4. Each row represents a layer, and each row's name is distinctive enough for us to refer to these layers without any confusion. As we can see, the figure has all of the layers that were added to the model in the preceding code sample. Each layer has an output, and the "Output Shape" column displays the shape of each output. The output from each layer serves as the first layer's input. You can see how many parameters have been trained for each layer in the

"Param #" column. At the conclusion, the total number of parameters—which includes both trainable and untrainable parameters—is displayed. All of the layers in this model can be trained.

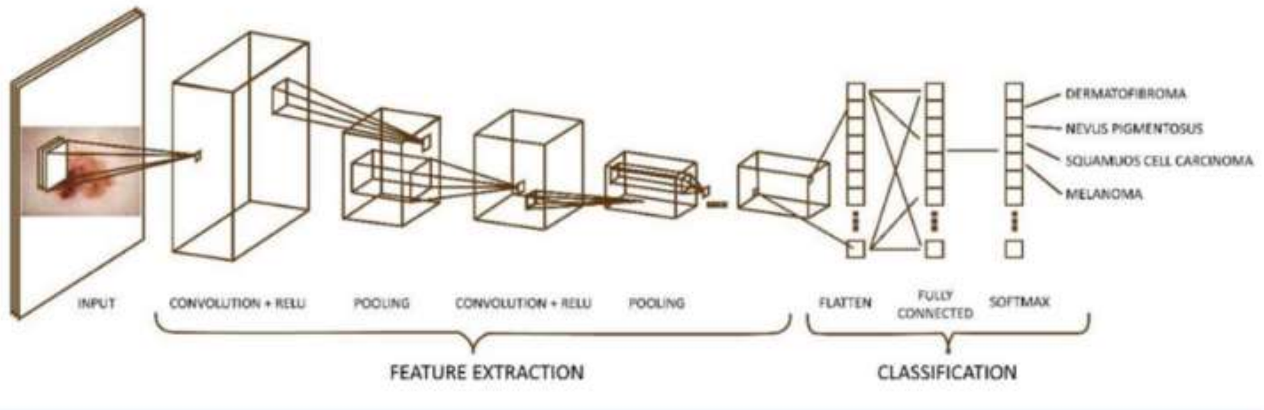

Figure 5: CNN Architecture

3.5 Model Accuracy

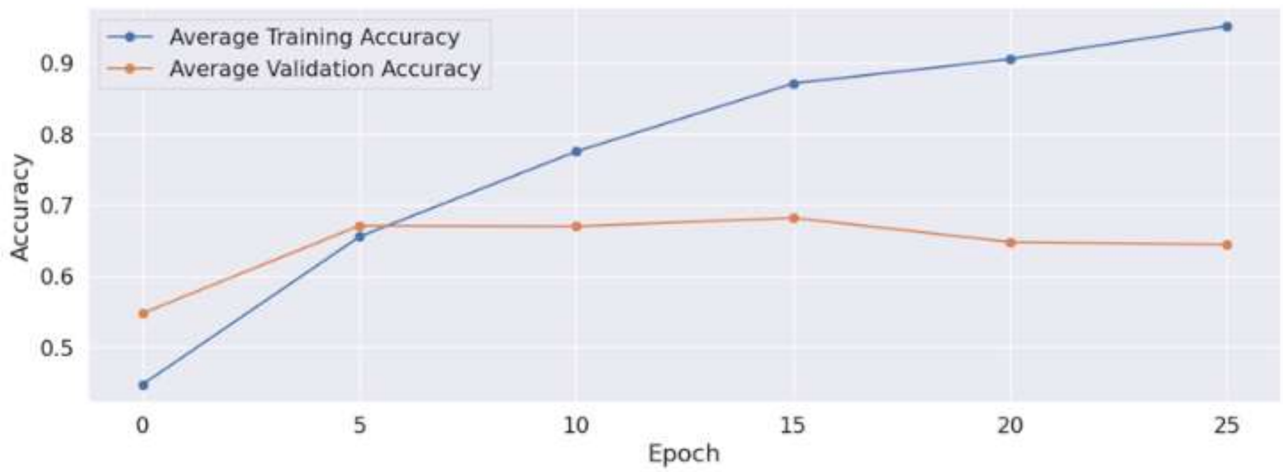

Figure 6: Training and Validation Accuracy

3.6 Model Loss

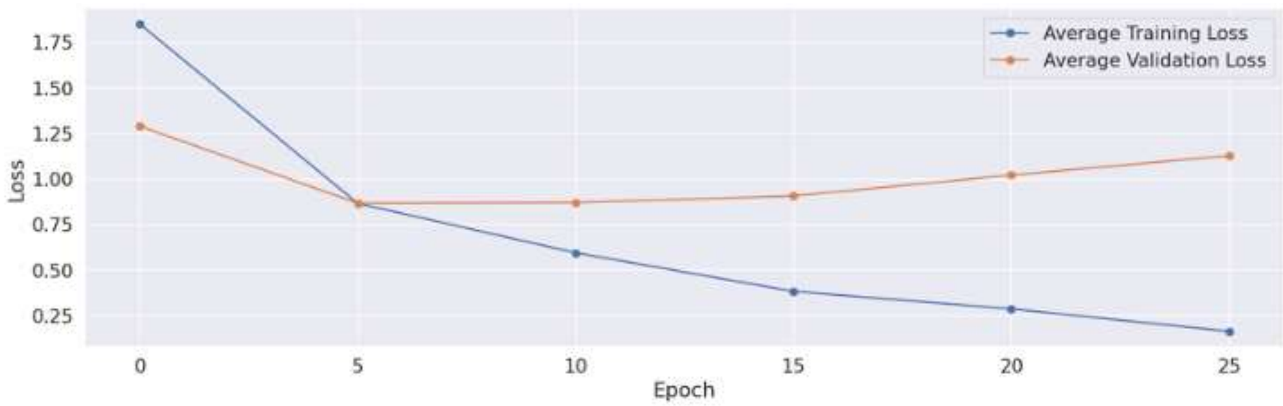

Figure 7: Training and Validation Loss

3.7 Confusion Matrix

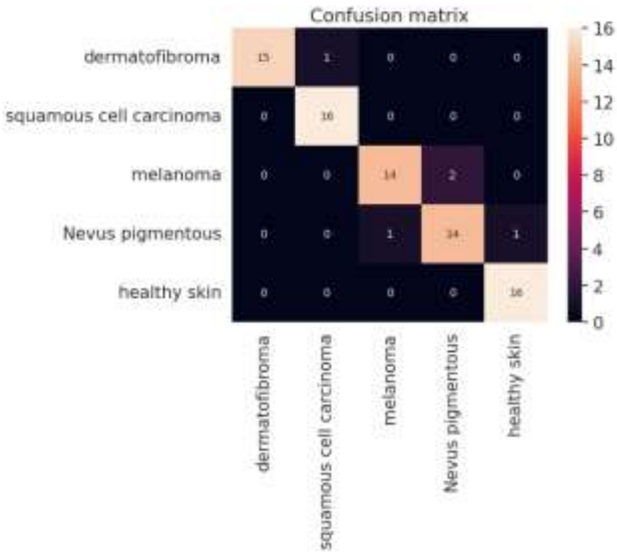

Figure 8: Confusion Matrix

4. Results

Based on the features passed to them, all the algorithms produced satisfactory results, with training accuracies ranging from 90% to 94%. The highest accuracy scores can be attributed to the feature extraction capabilities of the CNN architecture, combined with the Adam optimizer.

The CNN model effectively identified patterns in skin lesion images, enhancing classification accuracy. The convolutional layers extracted spatial features, while max pooling reduced dimensionality, preventing overfitting. The fully connected layers further refined classification by learning high-level representations of the lesions.

The model's performance demonstrated the effectiveness of deep learning in medical image classification. The use of Adam as an optimizer improved convergence speed and stability during training. The results indicate that CNN-based models can significantly aid in the automated detection and classification of skin lesions, providing valuable support for early diagnosis.

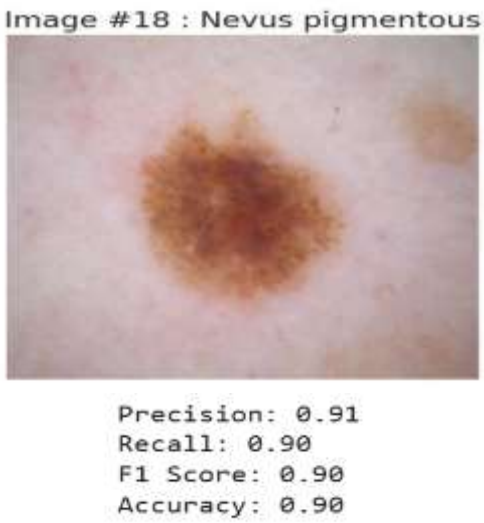

Figure 9: Prediction of Selected Image

5. Conclusion

The application of CNNs for skin cancer classification has demonstrated remarkable potential, marking a significant advancement in medical imaging and diagnostic accuracy. The ability of CNN models to accurately classify different types of skin cancer, including melanoma, can facilitate early detection and ultimately improve patient outcomes. Studies have consistently shown that CNN-based approaches surpass traditional machine learning classifiers and, in some cases, even expert dermatologists in diagnostic accuracy.

Despite these promising advancements, challenges remain. The availability of large and diverse datasets is still limited, and CNN models require greater interpretability and explainability to enhance trust in clinical settings. Additionally, potential biases in skin type classification must be addressed to ensure equitable healthcare solutions for all individuals.

Overall, CNN-based skin cancer classification represents an exciting and rapidly evolving research domain with the potential to revolutionize early detection and treatment, leading to improved patient prognosis and outcomes.

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