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Towards Accurate Detection and Classification of Skin Cancer Using AI-Powered Image Analysis

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Abstract- Context: Skin cancer is one of the most common and lethal forms of cancer if not diagnosed early. Detection at an early stage can mean a world of difference in survival. Despite advances in technology, most areas continue to face a lack of available dermatology specialists, making timely diagnosis a challenge. This gap between the need for early detection and the limited availability of experts highlights the urgency for automated, reliable diagnostic tools. **Objective:** In response to this need, the purpose of this work is to create a fast and accurate system for skin cancer detection that distinguishes between malignant and benign lesions. **Method:** This study, based on a Convolutional Neural Network (CNN), addresses some challenges, including limited data, image quality issues, and classification. **Results:** A balanced training set was used to train the model, which achieved a test accuracy of 88.60% and a macro-averaged Receiver Operating Characteristic Area Under the Curve (ROC-AUC) score of 0.95. Other significant metrics, such as precision, recall, and F1-score also validated the performance of the model. We developed a web-based interface to enable practical deployment and usability for real-world applications. **Conclusions:** The findings demonstrate the potential of deep learning techniques to enhance skin cancer detection and serve as a point of reference for future research on multi-class classification and real-time diagnostic platforms.

Keywords- Convolutional Neural Networks (CNNs), Deep learning, Image classification, Medical imaging, Skin cancer detection.

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1. Introduction

Skin is the largest organ of the human body, and it is present to protect us from other harmful chemicals and physical injury. Skin consists of three primary layers: the epidermis, dermis, and hypodermis. The outer epidermis serves as a buffer from the external world. Beneath it lies the dermis, which contains the connective tissue and sweat glands, followed by the hypodermis, composed of fat, serving as insulation and energy storage. In addition, the skin contains melanin, a pigment that absorbs UV radiation, protecting it from the damaging effects of UV rays [1].

Skin cancer arises as a result of abnormal growth of skin cells, which can metastasize to other parts of the body. It can be classified into three types: basal cell carcinoma, squamous cell carcinoma, and melanoma. Of these, the most perilous form is melanoma and it accounts for 75% of the mortality caused by skin cancer although it accounts for only 4% of cases [2]. Signs may include moles that vary in color, size, or shape, or moles that have irregular margins. Early melanoma detection is followed by very high survival rates. Early detection of melanoma remains an issue. In 2018, there were 287,723 new melanoma cases detected all over the world [3], resulting in 60,712 fatalities. In the United States, 2019 witnessed the development of around 96,480 new cases, leading to 7,230 deaths. Ultraviolet (UV) radiation resulting from exposure to sunlight is established as a significant skin cancer cause [4]. Basal cell carcinoma and squamous cell carcinoma are less prone to metastasize and are easier to treat, but melanoma's virulence necessitates treatment and identification at an early stage. Conventionally, the biopsy procedure is used to diagnose skin cancer by removing suspected skin tissues to be analyzed [5]. However, it is painful, time-consuming, and costly. The computer-based systems have advanced considerably in recent times to offer non-invasive tests for diagnosing symptoms of skin cancer [6]. These procedures include image acquisition, preprocessing, segmentation, feature extraction, and classification, thereby decreasing the complexity in diagnosis. Since the advent of artificial intelligence (AI), skin cancer detection has become more accurate and affordable. Deep learning, a branch of machine learning, employs multiple layers of neural networks to recognize patterns and structures in data [7]. A particular architecture called Convolutional Neural Networks (CNNs) is extremely good at visual image inspection. CNNs employ convolutional and pooling layers to model image features and hence are useful to identify skin cancer [8].

The importance of this research lies in the fact that it is extremely essential to design effective and efficient skin cancer detection systems with high accuracy that can assist in early diagnosis, thus guaranteeing improved patient outcomes. The research offers a solution towards overcoming the inherent challenges associated with skin cancer detection such as data availability being constrained, data quality, and discrimination among classes. The novelty of this work lies in its extensive use of CNNs for binary classification of skin lesions and how it can be adapted for multi-class classification tasks. In this work, a CNN-based model was implemented and validated using a balanced dataset to classify skin lesions as benign or malignant. The model's performance was validated using different metrics, and its feasibility in practical applications was confirmed. A web interface was also implemented to facilitate the practical implementation of the model, making it readily accessible to medical professionals and patients alike. This paper outlines the methodology, results, and avenues for future research towards developing skin cancer detection systems.

2. Related works

Recognizing melanoma, non-melanoma, and various types of skin lesions is a critical field of research, and recently different CNN-based methods have been proposed. [9] employed 2624 Universal Skin Imaging Coordinated Effort (ISIC) dermoscopic images. They applied transfer learning using AlexNet in addition to sparse coding, deep residual schemes, and convolutional U-networks. After performing the feature extraction via transfer learning, a support vector machine is used for classification, achieving 93.1% accuracy, 94.9% sensitivity, and 92.8% specificity for melanoma versus non-melanoma classification. [10] used only 399 images to classify melanomas versus nevus types. In their study, they used a pre-trained deep neural network (DNN). This dataset is relatively small for a task that requires sensitive client data. Their method achieves 92.1% sensitivity, 95.18% specificity, and 93.64% accuracy. [11] demonstrated a single CNN trained end-to-end for classifying skin lesions using only pixels and disease labels as inputs. They tested the performance on 2,032 different skin cancer cases and compared it against 21 board-certified dermatologists. Their model achieved accuracies of 69.4% and 72.1% for binary classification tasks involving carcinomas versus benign keratoses and melanomas versus benign nevi. [12] use ISIC 1600 images over 150 epochs to fine-tune a CNN model. They modify the last layer of ResNet for three classes, achieving accuracies of 96.90%, 97.00%, and 97.60%. [13] applied a set of state-of-the-art deep learning methods to identify diseases. Their ensemble consists of CNNs such as AlexNet, VGGNet, and GoogLeNet, which are renowned for winning the ImageNet challenge. They report accuracies of 79.3%, 79.9%, 81.2%, and 80.7% for various tasks. Respectively. [14] recommend a fully automated computerized method to classify skin lesions from dermoscopic images. Their novel ensemble scheme for CNNs combines intra-architecture features, achieving an accuracy of 87.3% for melanoma and 95.5% for seborrheic keratosis on the ISIC 2017 dataset. [15] proposed a deep learning framework for skin cancer detection that achieved promising results, yet the model's performance was constrained by the relatively small and imbalanced datasets used, highlighting the need for larger, more diverse datasets to improve robustness. [16] introduced an efficient seven-way multi-class classification system using MobileNet, emphasizing computational efficiency suitable for mobile applications. While this approach offers practical deployment advantages, it may sacrifice some accuracy compared to larger, more complex networks. [17] further explored deep learning methods tailored for mobile platforms, achieving accurate skin cancer recognition; nevertheless, challenges remain in balancing model complexity with resource constraints inherent to mobile devices. [18] provided a significant advancement in skin cancer classification by addressing class imbalance and leveraging ensemble deep learning. [19] advanced the field by employing ensemble learning techniques to enhance diagnostic accuracy, effectively mitigating individual model biases. Despite these improvements, ensemble methods often increase computational overhead and complexity, which can hinder real-time application.

While previous studies demonstrate the potential of CNNs for skin cancer detection, they also highlight several limitations:

1) Limited Dataset Sizes: Many studies utilize small datasets, such as 399 or 1000 images, which may not sufficiently represent the variability in real-world data.

2) Imbalanced Datasets: A lack of balanced class representation in datasets can lead to biased models that perform poorly on underrepresented classes.

3) Generalization Issues: Models trained on small or homogeneous datasets may fail to generalize to diverse patient populations or imaging conditions.

4) Lack of Comparative Analysis: Few studies provide comprehensive comparisons across different CNN architectures or preprocessing techniques.

To summarize, CNNs have been extensively applied for skin cancer and skin wound classification. However, there is a lack of publicly available datasets; many studies rely on small size of samples. In addition, there are few clinical image datasets, and generally, each study creates a new dataset for its purpose. To address this limitation, numerous CNN-based approaches employ transfer learning using pre-trained models such as AlexNet and many others. In this work, a CNN model based on MobileNet is trained using a large collection of multi-source dermoscopic images. Compared to previously proposed models, the MobileNet CNN has shown not only accurate and reliable performance but also faster inference time and a lightweight architecture suitable for mobile applications. As image size increases, the performance of MobileNet improves while maintaining a compact network size.

3. Motivation and objective

The motivation of this study is to address the current shortcomings identified within the literature on the basis of a more comprehensive dataset and employing an optimized CNN architecture for skin cancer screening. In the current study, we aim to:

1) Address the limitations of previous works, such as limited dataset sizes, imbalanced class representation, and generalization issues, by using a well-curated and balanced dataset.

2) Develop a robust system capable of detecting and classifying skin cancer from dermoscopic images with high accuracy and reliability.

3) Implement a CNN-based model optimized for skin lesion classification, ensuring scalability and adaptability for real-world scenarios.

4) Evaluate the model's performance using a comprehensive set of metrics, including accuracy, precision, recall, F1-score, and ROC-AUC, to provide an in-depth analysis of its effectiveness.

By fulfilling these objectives, this work seeks to advance the field of skin cancer detection and provide a reliable diagnostic tool for early melanoma identification.

4. Methodology

Based on the state-of-the-art review, and to address the challenges identified in the introduction, we propose a structured workflow that ensures effective skin cancer detection and classification. The workflow, illustrated in Figure. 1, involves several interconnected steps designed to enhance the system's overall performance:

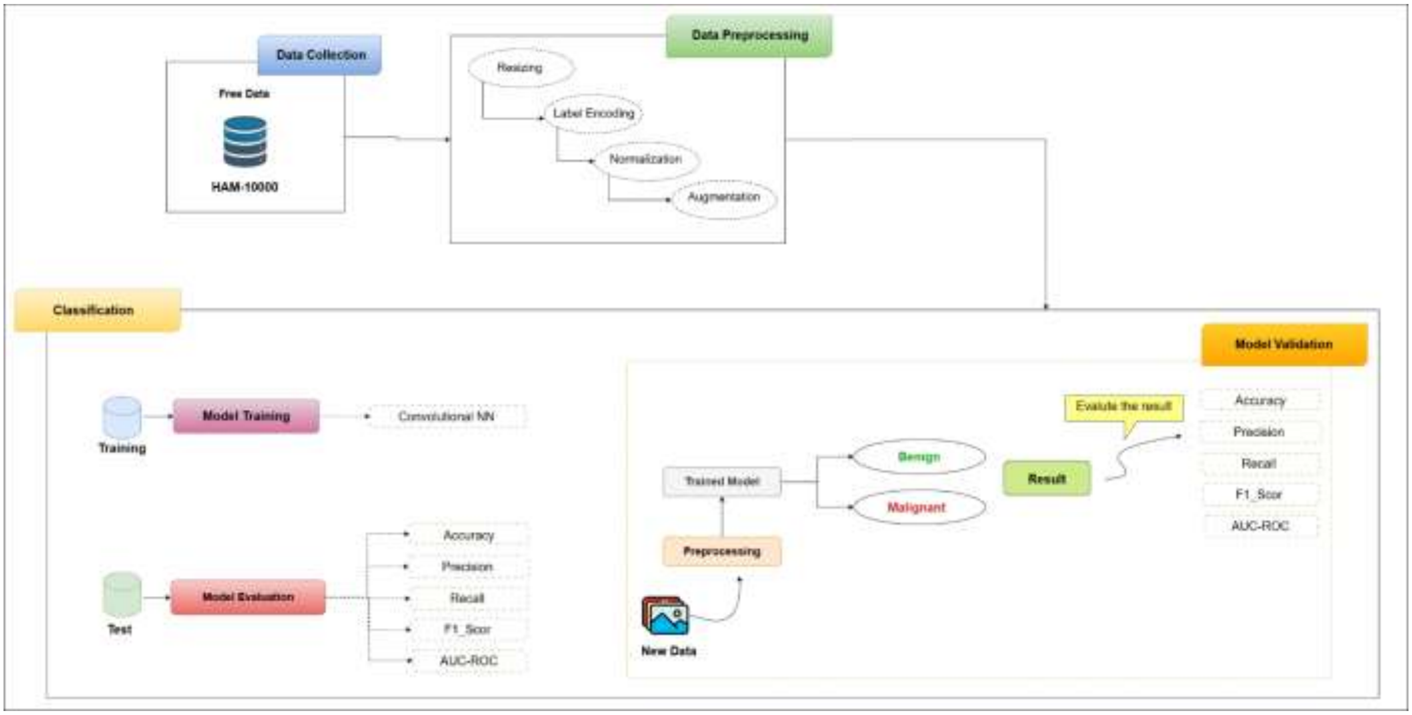


Figure 1. Our system workflow.

4.1. Data collection

In this step, we utilize the publicly available HAM10000 dataset [20] from Kaggle. This dataset comprises 9605 images designated for training the model and an additional 1000 images reserved for evaluating the model's performance. Each image is standardized to dimensions of 224×224 pixels and is represented in the RGB color scale. Figure 2 presents sample images from the training data. The dataset is balanced, with the test data containing 500 images per class (benign and malignant) Figure 3 presents the label distribution related to the testing data. For the training data, the dataset includes 5000 benign images and 4700 malignant images Figure 4 presents the label distribution related to the training data, ensuring sufficient representation for both classes.

Figure 2. Samples Images from the Training Data.

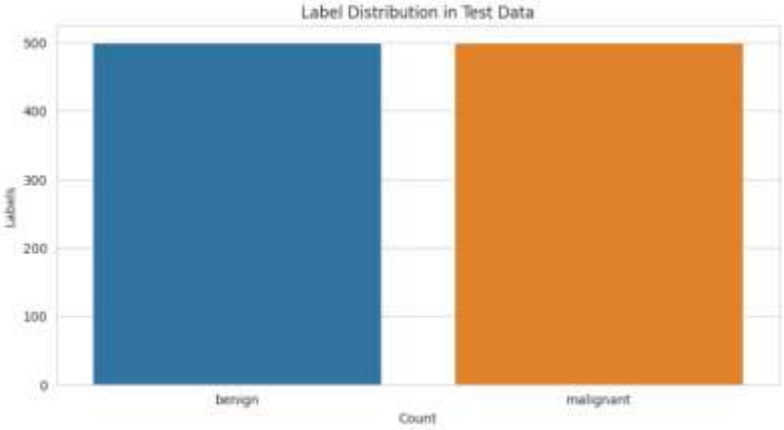


Figure 3. Label distribution in test Data.

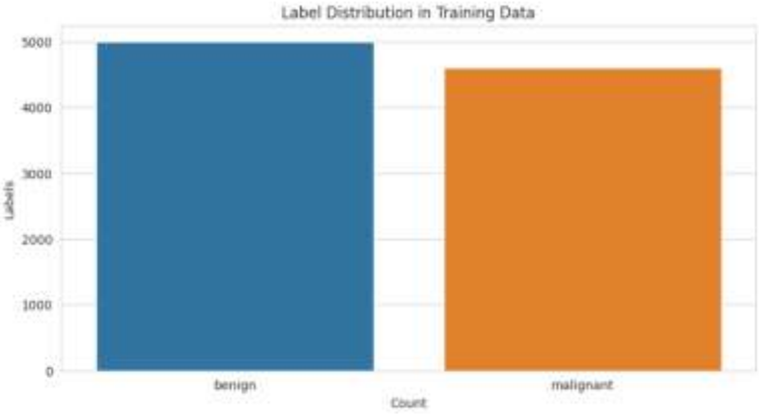


Figure 4. Label distribution in training Data.

4.2. Data preprocessing

After collecting the data, we applied preprocessing steps to prepare the images for training and testing. These steps ensure that the data is standardized and augmented to improve the model's generalization ability. The preprocessing includes:

1) Resizing Images : All images were resized to a consistent dimension of 224x224 pixels to match the input requirements of the CNN model.

2) Normalization : Pixel values were scaled to the range [0, 1],to speed up training, improve numerical stability and ensuring uniform intensity levels across all images.

3) Data Augmentation : To enhance the model robustness and reduce overfitting. We applied transformations such as:

- Random Rotations within a 20-degree range angle.
- Horizontal and vertical flipping
- Random zooming within a range of 0.2.
- Width Shift and Height Shift with range 0.2 .
- Brightness adjustments by range [0.8, 1.2].

4) Label Encoding : The class labels (benign and malignant) were one-hot encoded to align with the categorical cross-entropy loss function used in model training.

These preprocessing steps ensure that the dataset is consistent, diverse, and suitable for deep learning tasks. Figure 5 shows samples of the training data after the preprocessing step.

Sample Augmented Images from Training Data

Figure 5. Samples of training Data after Preprocessing.

4.3. Model design and training

Convolutional Neural Networks (CNNs) are a powerful tool for image classification, particularly in medical imaging. They can automatically learn important features from raw data, making them ideal for detecting subtle differences in skin lesions. CNNs are highly effective in handling high-dimensional data, capturing intricate patterns, and generalizing across diverse datasets. Motivated by these advantages, we developed a CNN model specifically tailored for the task of skin cancer detection, focusing on distinguishing between benign and malignant lesions.

The architecture of CNN model used in this study comprises the following layers and configurations, each selected to ensure optimal feature extraction and classification performance. Figure 6 presents the model architecture.

1) Input layer: Accepts images with a shape of (224, 224, 3), corresponding to the dimensions and RGB color channels.

2) First convolutional block: Convolutional Layer Conv2D with 32 filters and a kernel size of (3, 3), followed by ReLU activation, to extract low-level features such as edges and textures from the input images. Pooling Layer MaxPooling2D with a pool size of (2,2) to reduce spatial dimensions by half. A dropout rate of 0.25 was applied to prevent overfitting.

3) Second convolutional block:

Conv2D Layer with 64 filters and a kernel size of (3,3), followed by ReLU activation, to Captures more complex patterns and higher-level features. Pooling Layer MaxPooling2D with a pool size of (2,2) to further reduce spatial dimensions. A dropout rate of 0.25 was applied.

4) Flattening layer: Converts the 2D feature maps into a 1D feature vector to serve as input for the fully connected layers.

5) Fully connected layers: Dense Layer Contains 128 neurons with ReLU activation to learn high-level representations. A dropout rate of 0.5 was applied to reduce overfitting by randomly deactivating neurons.

6) Output layer: dense layer contains a number of neurons equal to the number of classes (2 in this case: benign and malignant) with softmax activation. The Outputs class probabilities for classification.

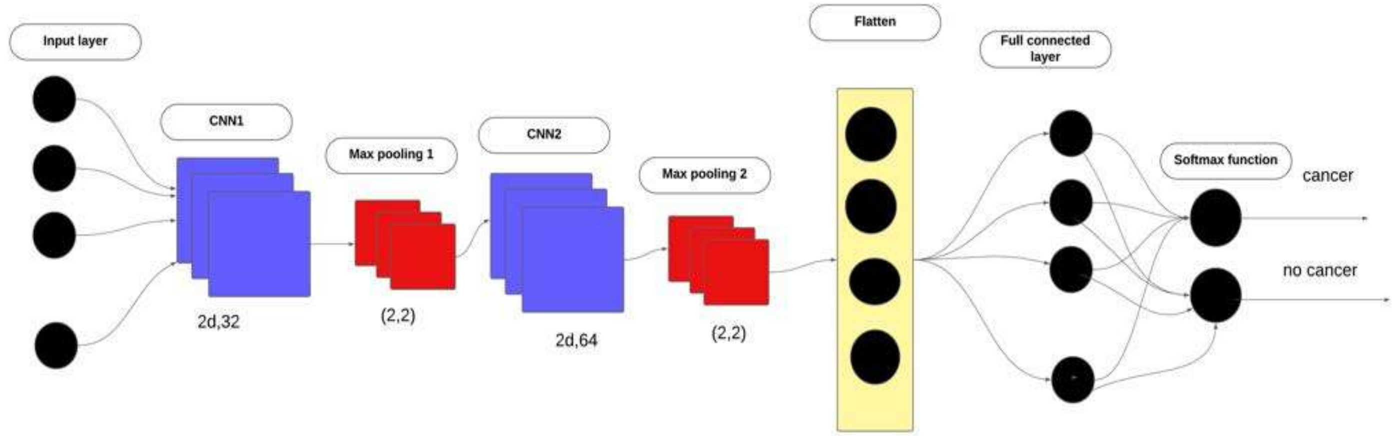


Figure 6. CNN model architecture.

The model was compiled with the Adam optimizer (learning rate = 0.001), the categorical cross-entropy loss function, and accuracy as the evaluation metric. Figure 7 presents the CNN Model parameters summary.

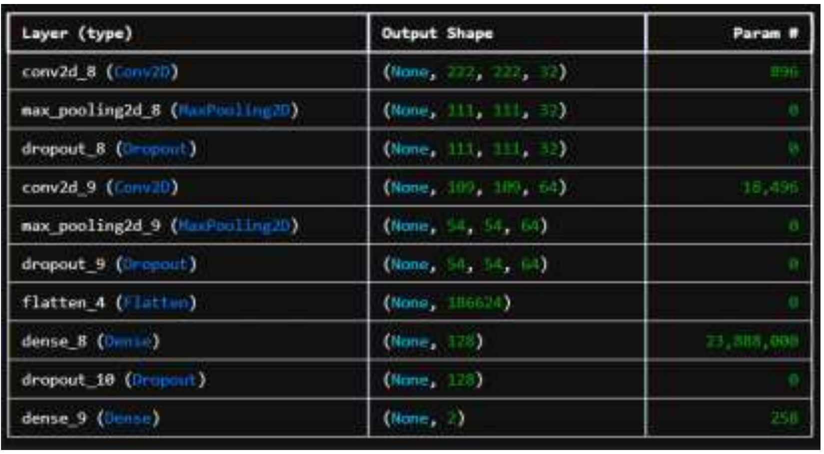
To train the CNN model , we employed the following configuration:

- Batch Size of 32 was used to balance computational efficiency and gradient update frequency.

- The model was trained for 10 epochs, which was sufficient for convergence given the dataset size and preprocessing applied.

- A learning rate of 0.001 was chosen to ensure stable and efficient optimization.

- The Adam optimizer was used for its adaptive learning capabilities and computational efficiency.



Layer (type)	Output Shape	Param #
conv2d_8 (Conv2D)	(None, 222, 222, 32)	896
max_pooling2d_8 (MaxPooling2D)	(None, 111, 111, 32)	0
dropout_8 (Dropout)	(None, 111, 111, 32)	0
conv2d_9 (Conv2D)	(None, 109, 109, 64)	18,496
max_pooling2d_9 (MaxPooling2D)	(None, 54, 54, 64)	0
dropout_9 (Dropout)	(None, 54, 54, 64)	0
flatten_4 (Flatten)	(None, 186624)	0
dense_8 (Dense)	(None, 128)	23,888,000
dropout_10 (Dropout)	(None, 128)	0
dense_9 (Dense)	(None, 2)	258

Figure 7. CNN model parameters summary.

- We reserved 20% of the training data for validation, to monitor the model's performance during training and prevent overfitting.

4.4. Model evaluation

After completing the model's training step, we evaluated the performance of the trained model on the test dataset to assess its effectiveness in detecting skin cancer (benign or malignant). We conduct the evaluation using a set of performance metrics, including accuracy, precision, recall, F1-score, and the Receiver Operating Characteristic Area Under the Curve (ROC-AUC), as defined respectively, in equations (1)-(5). Where TP stands for True Positives, (i.e., correctly predicted positive samples), TN stands for True Negatives (i.e., correctly predicted negative samples), FP stands for False Positives (i.e., incorrectly predicted positive samples), FN stands for False Negatives (i.e., incorrectly predicted negative samples), TPR stands for True Positive Rate and FPR stands for False Positive Rate.

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN} \tag{1}$$

$$Precision = \frac{TP}{TP+FP} \tag{2}$$

$$Recall = \frac{TP}{TP+FN} \tag{3}$$

$$F1 - score = 2x\frac{\text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}} \tag{4}$$

$$AUC = \int_0^1 TPR(FPR)d(FPR) \tag{5}$$

The CNN model achieved notable results, with a test loss of 0.2905 and a test accuracy of 88.60%, demonstrating stable convergence, as shown in Figure 8. Additional metrics, as detailed in the classification report in Table 1, include precision, recall, and F1-score for each class.

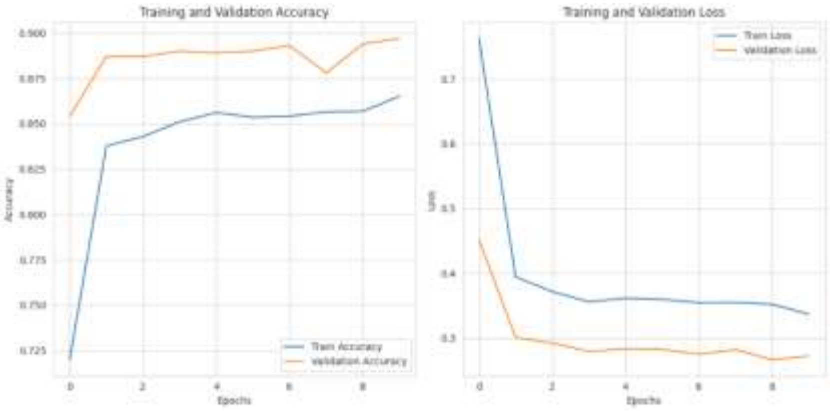


Figure 8. Training and validation accuracy and loss

Table 1. Classification Report for the CNN Model

Class	**Precision**	**Recall**	**F1-Score t**	**Support**
0 (Benign)	0.8535	0.9320	0.8910	500
1 (Malignant)	0.9251	0.8400	0.8885	500
Accuracy	Accuracy 0.8860 (1000 total)			
Macro Avg	0.8893	0.8860	0.8858	1000
Weighted Avg	0.8893	0.8860	0.8858	1000

Additionally, the confusion matrix, shown in Figure 9, provides further insights into the model's classification performance, with accurate classification of 466 benign and 424 malignant lesions, alongside some misclassifications (34 benign being recognized as malignant and 76 malignant being recognized as benign). The relatively higher number of false negatives remains a concern in the medical context, because missed cancer cases could postpone lifesaving treatment. This outcome suggests that while the model is proficient in distinguishing benign lesions, additional strategies, such as incorporating more diverse malignant samples, fine-tuning thresholds, or integrating attention mechanisms, might be necessary to further enhance sensitivity and reduce false negatives, and make the system safer and more dependable for doctors and screening programs.

Furthermore, the model achieved a macro-averaged ROC-AUC score of 0.95, indicating its excellent ability to distinguish between the two classes. The ROC-AUC curve presented in Figure 10 highlights the model's strong capability in differentiating between benign and malignant cases.

The CNN model demonstrated robust performance in detecting and classifying skin lesions. The balanced dataset and careful preprocessing steps significantly contributed to this strong performance.

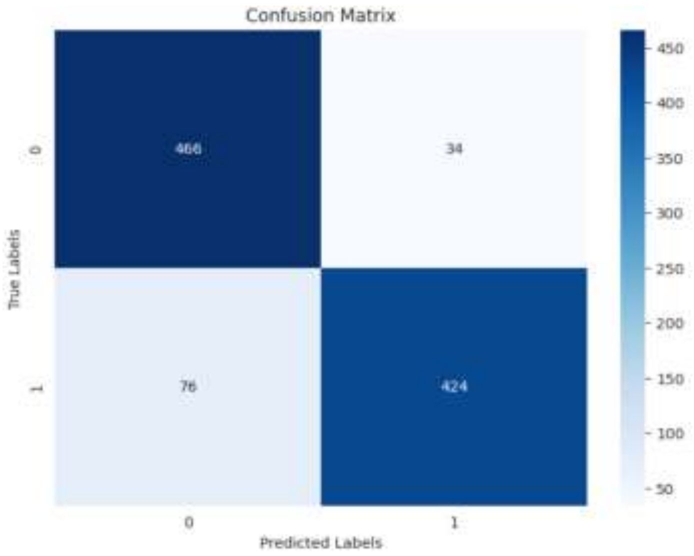


Figure 9. The confusion matrix

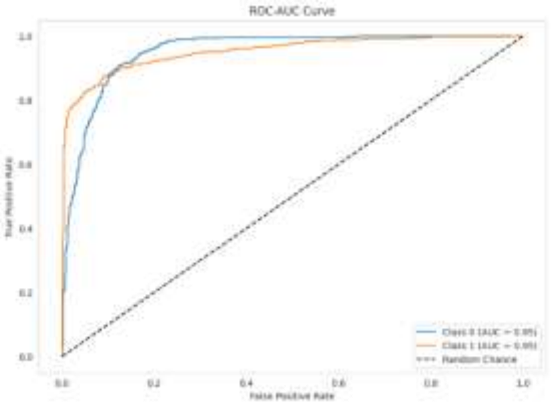
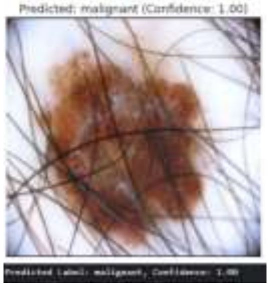


Figure 10. AUC-ROC Curve

4.5. Model validation

In the final step of the workflow, we tested the trained CNN model on completely new data to evaluate its ability to generalize to unseen cases. This new data consisted of images sourced from medical websites or real-world images captured directly. These images were processed and fed into the trained model, and the predicted labels were compared with the known ground-truth labels to assess the model's performance. An example of correct recognition is shown in Figure 11 ensuring that the power of the model extends beyond the test dataset, providing a realistic measure of its applicability in real-world scenarios.



```
Predicted Label: malignant, Confidence: 1.00
```

Figure 11. Example of validation

The CNN model demonstrated robust performance in detecting and classifying skin lesions. The model's high accuracy, precision, recall, F1-score, and ROC-AUC scores validate its reliability and effectiveness. The balanced dataset and careful preprocessing contributed to this strong performance. However, minor misclassifications were observed, indicating potential areas for improvement, particularly in edge cases where lesions exhibit characteristics of both benign and malignant classes. Future enhancements could include:

- Incorporating additional preprocessing techniques to highlight lesion-specific features (segmentation).

- Exploring advanced architectures such as EfficientNet or Vision Transformers to further improve classification performance.

- Expanding the dataset to include more diverse examples, which could improve generalization to real-world scenarios.

Overall, the proposed CNN model serves as a reliable framework for skin cancer detection and classification, providing a foundation for future advancements in this critical field.

5. Comparison with Prior Work Using the HAM10000 Dataset

Numerous studies have employed the HAM10000 dataset to develop skin cancer classifiers based on convolutional neural networks (CNNs), transfer learning, and pre-trained models. These approaches vary in terms of architectures used, preprocessing techniques, and performance metrics. In the following, we summarize some key contributions from recent studies:

- [15] applied transfer learning using AlexNet as a pre-trained model. Their method achieved an AUC of 0.91, with an accuracy of 84%, sensitivity of 81%, and specificity of 88%.

- [16] employed MobileNet with transfer learning, achieving 83.1% classification accuracy.

- [17] explored various CNN architectures and identified DenseNet169 as the most effective, with an accuracy of 92.25%. Their work also included the development of a mobile application for skin lesion detection.

- [18] addressed class imbalance using data augmentation techniques and compared the performance of AlexNet, InceptionV3, and RegNetY-320. Among these models, RegNetY-320 yielded the highest accuracy of 91%.

- [19] evaluated several pre-trained models including MobileNetV2, ResNet18, and VGG11 on the HAM10000 dataset, reporting accuracies of 79.8%, 80.2%, and 80.5%, respectively. Using ensemble methods, their proposed SkinNet model achieved an improved accuracy of 86.7% and an AUC of 0.96.

In comparison, our proposed CNN model achieved an accuracy of 88.6%, which indicates a relative improvement over several methods using the HAM10000 dataset, as shown in Table 2. This enhanced performance may be attributed to effective preprocessing strategies, the use of balanced class distributions, data augmentation, and optimal architectural choices. Our model's ROC-AUC of 0.95 matches matching that of [18] and [19] and outperforms [15] indicating its strong discrimination ability.

Table 2. Comparison of Deep Learning Models for Skin Cancer Classification on HAM10000 Dataset

Study	Model / Architecture-	Accuracy (%)	Precision (%)	F1-score (%)	ROC-AUC
[15]	AlexNet	84.00	/	/	0.91
[16]	MobileNet	83.10	89.00	83.00	/
[17]	DenseNet169	92.25	/	93.27	/
[18]	RegNetY-320	91		88.10	0.95

[19]	Ensemble learning (SkinNet)	86.70	/	/	0.96
Proposed work	Proposed CNN	88.60	88.93	88.58	0.95

This comparative analysis highlights the robustness of our proposed model and underscores its competitive performance on the HAM10000 benchmark.

6. Web application

In our web application, we developed an interactive and user-friendly interface for skin cancer detection using the Next.js framework for the frontend and Tailwind CSS for styling and design. The application is designed for ease of use and does not require authentication or login.

Users can directly upload an image of a skin lesion and receive a prediction from the AI model. The interface provides:

- A clear confidence percentage indicating the likelihood of malignancy or benignity.

- Detailed visualization of the AI detector's confidence level, helping users better understand the prediction results.

For the Backend Implementation, we utilized FastAPI, a modern Python framework, to build a secure and efficient API. The API processes the uploaded images, communicates with the AI model for predictions, and delivers the results to the user interface. A MySQL database is used to store processed data temporarily, ensuring smooth and reliable communication between the frontend and backend systems. Figures 12–14 present screenshots of the web interface.

Figure 12. Homepage Interface for Skin Cancer Detection

Figure 13. Homepage following Interface for Skin Cancer Detection

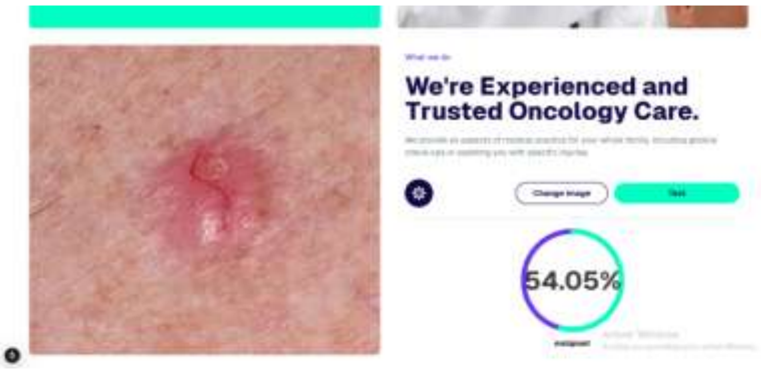


Figure 14. Results Displayed After Uploading an Image

7. Conclusion and future work

This research highlights the potential of Convolutional Neural Networks (CNNs) in transforming skin cancer diagnosis, particularly in distinguishing between benign and malignant lesions. By using a sufficiently balanced dataset and stringent preprocessing procedures, the model achieved very good accuracy and had excellent generalization ability. Precision, recall, F1-score, and ROC-AUC measures further validated its reliability, enhancing its prospects for deployment in real-world application. Aside from the technical achievement, a user-friendly web interface was developed to make the model accessible, closing the gap between state-of-the-art research and clinical application. The application of deep learning to clinical diagnostics is providing a non-invasive, time-saving, and cost-effective approach to the early detection of skin cancer, lessening the need for conventional biopsy interventions and bringing timely diagnosis within grasp.

Nevertheless, there are issues like the availability of high-quality data, variability in images, and complexity in the classification of different kinds of lesions. Future directions include expanding the size of the dataset, enhancing preprocessing techniques, and employing hybrid models comprising CNNs and transformers for better performance. Additional modification of the model for enabling multi-class classification, enabling real-time detection, and deployment on mobile or edge devices will enhance its potential even further. In short, this research is a critical stepping stone for AI-driven healthcare technologies, with the vision of a future where detection of skin cancer, at an earlier and more accurate stage, is more accessible and dependable. This study lays a foundation for future research that can enhance patient outcomes and even lives saved.

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