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Review RRJoOH

CNN-Based Diagnosis of Skin Cancer from Dermoscopic Images

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Abstract

Skin cancer has become one of the diseases widely spread over the globe, with melanoma becoming a severe threat to one's health. Detection of such diseases at the initial stage saves an individual from drastic damage. Using a Convolutional Neural Network (CNN) for detecting skin cancer through image classification as benign or malignant provides significant support to dermatological practice and reduces dependence solely on subjective visual examination. Dermatologists often face diagnostic challenges because early-stage lesions may closely resemble harmless conditions, and visual interpretation can vary depending on clinical experience. To overcome these diagnostic variations and improve reliability, this research proposes a robust computer-aided detection (CAD) framework based on a multi-layered CNN architecture. The system automatically extracts relevant features, such as asymmetry, border irregularity, color variation, and texture patterns from dermoscopic images without the need for manual feature engineering. By learning hierarchical representations of lesion characteristics, the model enhances diagnostic accuracy and assists clinicians in early screening. This approach aims to function as a supportive decision-making tool, enabling faster evaluation, reducing human error, and facilitating timely identification of potentially malignant lesions, ultimately contributing to improved patient outcomes and more efficient dermatological care.

Keywords: Clinical, CNN, deep learning, melanoma, skin cancer

INTRODUCTION

Skin cancer is one of the prominently increasing diseases globally, primarily because of ultraviolet radiation from both sun rays and artificial sources. As incidence rates grow across nearly every demographic, the treatment methods narrow. Detecting the melanoma in an early stage precisely is no longer a goal but a need to improve survival rates.

This research aims to mitigate this problem by designing a system that predicts the occurrences of skin cancer. Traditional diagnoses, like dermoscopy and visual inspection, are somewhat limited. These methods significantly rely on the knowledge of the practitioner, which often leads to human error and delayed treatment at places where no facilities are available. People in far-away places cannot get beneficial healthcare during a time of need.

The rise of AI gave a new version of computer-aided treatment to support dermatological assessments. CNN excels in image processing and classification so that it is used specifically for analyzing the image. We used dataset HAM10000 from Kaggle to train the model on images of a variety of skin lesions to make it easy for detecting the benign or malignant nature of the disease. Furthermore, we examine the essential role of image preprocessing, data augmentation, and segmentation in stabilizing model performance.

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RELATED WORKS

In early years, the diagnosis totally relies on the dermatologists for predicting the diseases. At some places, it becomes difficult to get treatment because of scarcity of medical equipment in far-away places. This problem is mentioned in the paper documented by Brinker et al. and Celebi et al. [1, 2]. The idea of using CNN for detecting skin lesions was proposed by Esteva et al. (2017) [3]. He said that CNN could also achieve the same level of expertise as a dermatologist-level assessment. This also gave a scope to superior alternatives to classical machine learning and handcrafted diagnosis. This change was for helping the dermatologist with their work as an assistant.

He et al. and Haung et al. [4, 5] mentioned the transfer learning in their studies because of the scarcity of the image datasets on the skin lesions. As CNN gives a low accuracy rate, to increase the accuracy of the system. It is used along with SVM to make it stable for multi-class discrimination in benign or malignant.

Setiawan et al. [6] used CLAHE and MSRCR for the CNN model for improving the picture/image quality that is used for prediction. A poor-quality picture was a barrier to the accuracy of the prediction of the disease. Attention-based models, addressing the interpretability gap of CNN, were introduced by Zhang et al. [7]. It focuses on the region of interest. Matsunaga et al. and Xie et al. [8, 9] proposed the use of segmentation-based framework to reduce the effect of the “black box,” allowing the clinicians to understand decision triggering areas. Rise in telemedicine gave way to lightweight CNNs optimized for mobile devices, which enables real-time screening. This is introduced by Goyal et al. [10] in his paper. Federated and collaborative learning protects the patient’s privacy and still benefits from distributed datasets simultaneously (Table 1).

Table 1. Comparison of deep learning models for skin lesion classification.

Author/year	Model used	Dataset	Accuracy	Key distribution
Esteva et al. (2017) [3]	InceptionV3	ISIC	94.5%	Dermatologist-level classification of melanoma.
Brinker et al. (2019) [1]	ResNet50	HAM 10000	95%	Comparison of CNNs for melanoma detection.
Goyal et al. (2023) [10]	MobileNetV2	HAM 10000	93%	Lightweight CNN for mobile-based diagnosis.
Setiawan et al. (2020) [6]	CNN + Color Enhancement (CLAHE/MSRC R)	ISIC	90%	Studied impact of color enhancement on early-stage skin cancer detection.
Zhang (2021) [7]	CNN	Kaggle	91%	Automated melanoma detection using standard CNN pipeline.
Zhang et al. (2023) [4]	NA	NA	NA	Compared basal cell carcinoma microenvironment to other malignancies.

TECHNOLOGY USED

Software Components

The software tools and development environment utilized for building and testing the proposed system are summarized in Table 2.

Table 2. Software components used in the skin lesion classification system.

Software	Description
Python 3.10+	Core programming language.
TensorFlow / Keras	For deep learning model implementation.
NumPy, Pandas	For data manipulation and numerical computation.
OpenCV, Matplotlib	For image preprocessing and visualization.
Flask	For building a web-based interface.
Jupyter Notebook / VS Code / Google Colab	IDE for development and testing.

Hardware Components

The hardware specifications required to run and train the proposed system are presented in Table 3.

Table 3. Hardware requirements for the skin lesion classification system.

Component	Specification
Processor	Intel Core i5/i7 or AMD Ryzen 5 and above.
RAM	Minimum 8 GB (16 GB recommended).
GPU	NVIDIA GPU with CUDA support (optional but accelerates training).
Storage	50 GB or more.
Operating System	Windows 10/11 or Linux.

SYSTEM OVERVIEW

The system architecture includes four steps to train the model accurately (Figure 1).

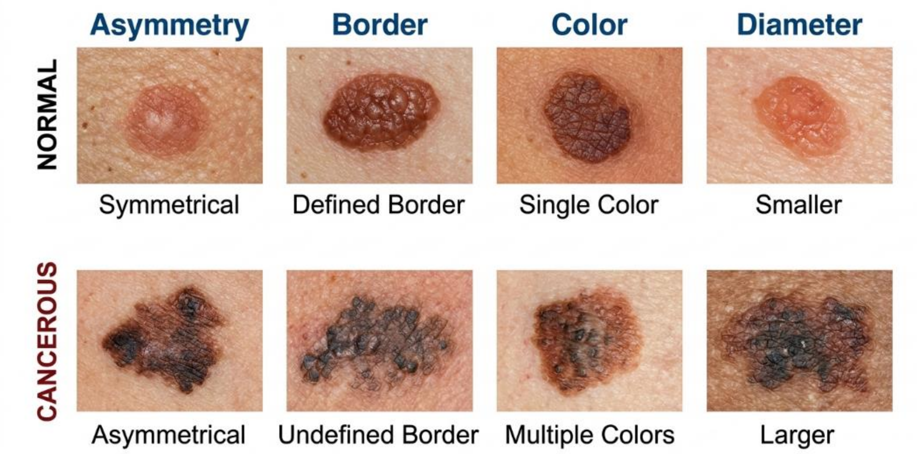

Figure 1. ABCD rule illustrates normal vs malignant skin lesions.

Data Acquisition and Neural Preprocessing

The first step begins with collecting the data from various platforms. We use the dataset HAM10000 in the model to make the dataset diverse and include varied skin tones. This step includes:

- Reducing the size of the image pixel.
- Reducing the noise in the data.

Data Augmentation

To balance the *data* and prevent overfitting, the image versions are slightly changed by rotating them, flipping them, and zooming in and out.

Feature Extraction and Convolutional Layers

After preprocessing, the images are sent to CNN. This part teaches us to recognize the patterns in the images to detect skin lesions.

Initial CNN layers help in detecting simple features like edges, colors, and textures. Deep learning of CNN is used to identify complex features like vascular structure, lesion shapes, and pigmentation patterns. Max pooling is used in between layers for:

- Reducing the size of the image.
- Lower computation.
- Keeping important information.

Activation Function (ReLU) helps the model to learn complex, non-linear mappings of the data.

Classification and Optimization

Figure 2 depicts skin lesion classification pipeline from augmentation to benign/malignant detection.

The information is flattened and sent to the dense layers once the important features are extracted by CNN. The dense layers make the final decision about the types of skin lesions. A softmax layer is used to convert result into probabilities of each class (e.g., benign or malignant). The model iteratively adjusts the weight by reducing the cross entropy-loss function during the training. It is obtained using Adam optimizer, performing backpropagation to adjust the parameters based on the gradient of the error.

Performance Evaluation

After this, the model is tested on unseen images to check the reliability of the system. It is validated by a few metrics scores, including F-1 score, accuracy, precision, and recall (sensitivity). Furthermore, it includes confusion metrics, which identify specific class-wise misclassification, ensuring the system does not miss any malignant cases, as it is most critical (Figures 2 and 3).

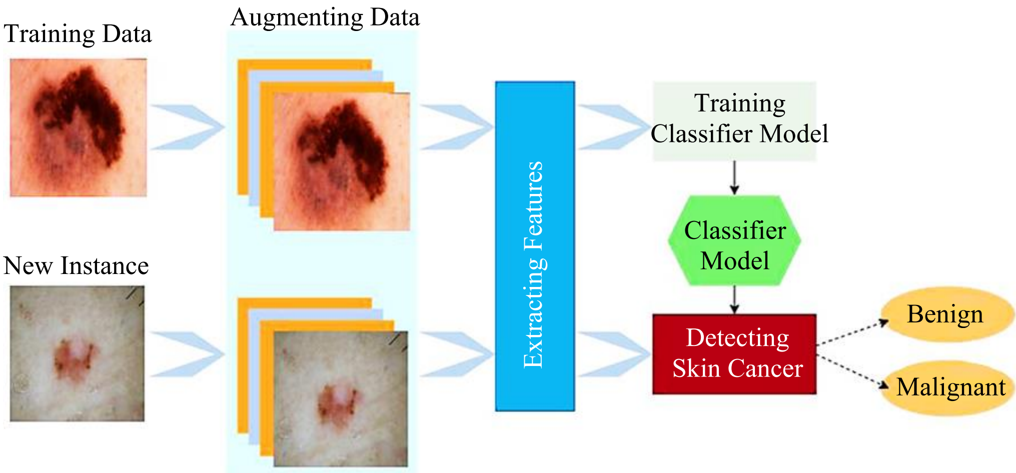

Figure 2. Deep learning pipeline for skin cancer classification.

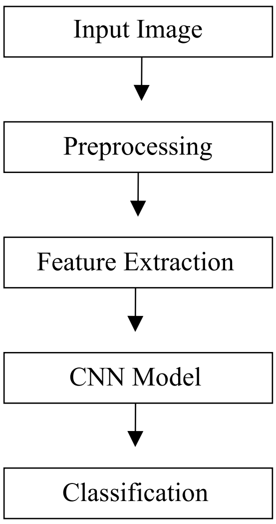

Figure 3. CNN workflow for skin lesion classification.

Performance Graph

The classification performance of the model for each lesion category is illustrated in Figure 4, where most samples are correctly predicted along the diagonal, indicating good overall accuracy and limited misclassification.

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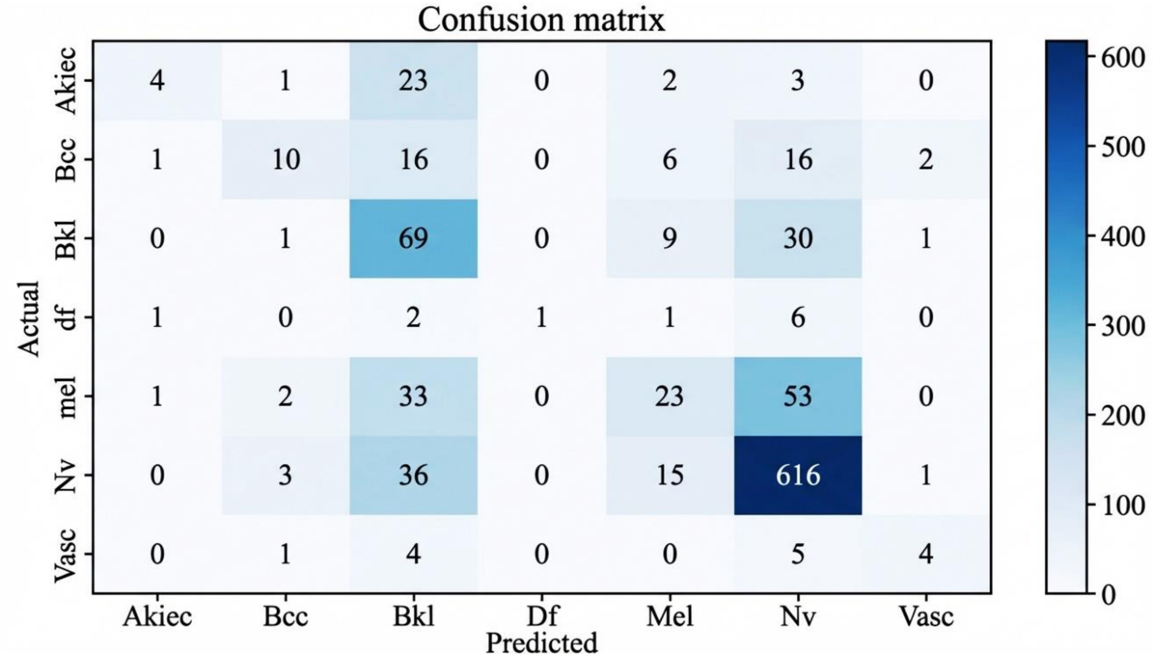

Figure 4. Confusion matrix of the proposed skin lesion classification model.

Loss Curve

Figure 5 shows the variation of training and validation accuracy during model training. The training accuracy gradually increases, while validation accuracy stabilizes with minor fluctuation, indicating effective learning with limited overfitting.

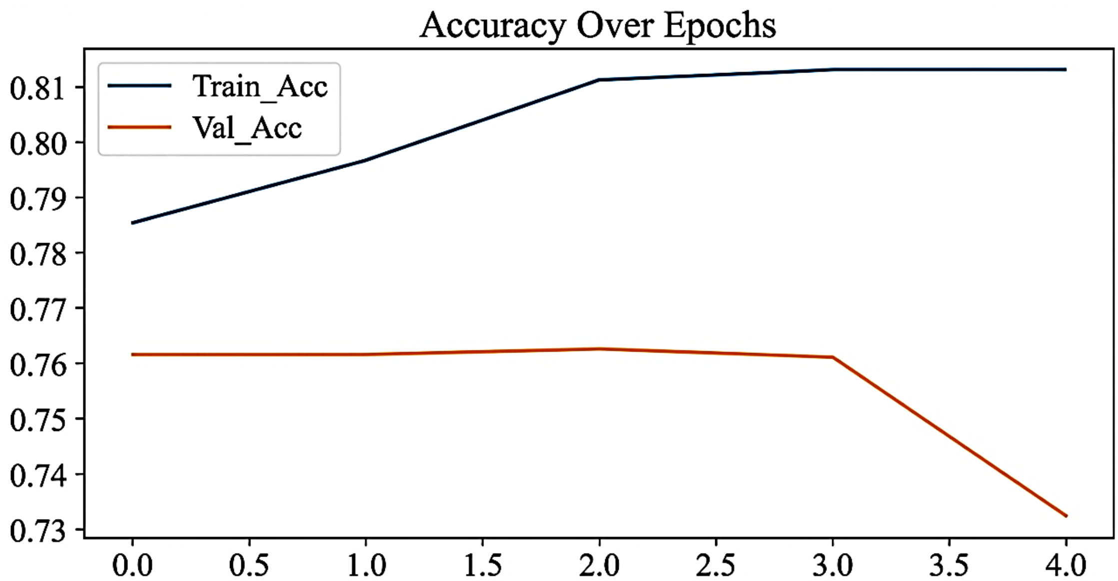

Figure 5. Training and validation accuracy curves over epochs.

RESULT & DISCUSSION

The model's performance is tested on unseen HAM1000 and Kaggle. It includes the suite of accuracy, precision, recall, and F-1 score to check the system reliability. The accuracy matters for the system, but it is not everything. Missing a single diagnosis is critical, so recall is important to not miss any malignant case. In dermatological terms, recall is important because it tells us that a false negative is worse than a false positive. And accuracy can be high due to class imbalance, might cause a misdiagnosis. The evaluation metrics of the system are given below in Table 4.

Table 4. Evaluation of the model.

Metric	Result
Accuracy	0.90
Precision	0.90
Recall	0.88
F1-Score	0.89

The proposed CNN model's performance proved that with deep learning we can bridge the gap between clinical analysis and computer prediction. We have trained the model on large dataset with different types of skin tones such that it makes our model work on skin tones effectively.

CONCLUSION AND FUTURE STUDIES

Deep learning using CNN has reformed the way to detect skin cancer by machines. The results provided by the machine are accurate and practical enough to be used outside of research labs. The developed model achieved approx. 90%, indicating that deep learning-based dermatological assessment can provide reliable decision support. We used EfficientNetB0 with ImageNet pertaining and added a custom fully connected classifier for 7 skin types. But high accuracy is not everything, there is a major obstacle to the model is that it often works like a "black box" making decision that cannot be explained by experts. To resolve the issue, we included preprocessing and interpretability features so it can easily be understood why model made certain predictions. This makes it easier to trust and use in real-life scenarios. And another challenge is fairness, where enough data for different skin tones is scarce, which can lead to biased predictions. Instead of just using techniques like oversampling, prospects should include large and varied datasets that include people from different ethnic backgrounds and rare lesion types. It will make it more accurate and fairer for everyone. Overall, the goal of the framework is to make high quality diagnosis which is accessible to everyone reducing human error and expert-level assessment of patients.

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