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An Enhanced Convolutional Neural Network for Classification of Melanoma Skin Cancer

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ABSTRACT
Melanoma is one of the most aggressive forms of skin cancer and accounts for a disproportionately high number of skin cancer–related deaths despite its relatively low incidence. Early and accurate diagnosis is therefore essential for improving patient survival rates. This study presents an enhanced Convolutional Neural Network (CNN)-based approach for automated melanoma classification using dermoscopic images. The proposed model was developed using the HAM10000 dataset, which contains 10,015 labeled dermoscopic images categorized into melanoma and non-melanoma classes. Comprehensive preprocessing techniques, including image resizing, normalization, and data augmentation, were employed to improve model generalization and reduce overfitting. The CNN architecture integrates convolutional and pooling layers for hierarchical feature extraction, dropout layers for regularization, and a Softmax output layer for classification. The model was trained using the Adam optimizer with a learning rate of 0.001, a batch size of 32, and 100 epochs, employing an 80/20 training–testing split with 10-fold cross-validation. Experimental results show that an enhanced CNN achieved an accuracy of 96.5%, with precision, recall, and F1-score values of 96.9%, 96.0%, and 96.4%, respectively. The model outperformed baseline CNN models and selected pre-trained architectures such as ResNet50. These results demonstrate the robustness and effectiveness of the enhanced approach, highlighting its potential for integration into computer-aided diagnostic systems to support dermatologists in early melanoma detection.

Keywords:
Melanoma skin cancer;
Convolutional neural Network;
Deep learning;
Dermoscopic images;
Medical image Classification;
HAM10000 dataset

INTRODUCTION

Skin cancer is the most commonly diagnosed cancer worldwide, with melanoma being its most aggressive and life-threatening form. Melanoma is characterized by rapid metastasis and resistance to conventional therapies in advanced stages, making early detection crucial for improving patient survival rates (Brinker et al., 2023). Despite advancements in dermatological practice, distinguishing melanoma from benign skin lesions remains challenging due to visual similarities, often resulting in misdiagnosis or delayed treatment.Traditional diagnostic procedures, such as dermoscopy followed by biopsy, are effective but invasive, time-consuming, and often inaccessible in resource-limited settings. Consequently, there is a growing demand for automated, accurate, and non-invasive diagnostic solutions.Recent advances in artificial intelligence, particularly deep learning, have significantly transformed medical image analysis. Convolutional Neural Networks (CNNs) have demonstrated remarkable performance in image classification tasks by automatically learning discriminative features from raw image data (Esteva et al., 2017; Abbas et al., 2023). This study proposes a CNN-based model for melanoma skin cancer classification using dermoscopic images, with the aim of providing a reliable diagnostic support tool that enhances clinical decision-making and improves accessibility to early detection.Melanoma arises from genetic mutations in melanocytes, most commonly involving the BRAF and NRAS genes (Lippincott Williams & Wilkins, 2022). Prolonged exposure to ultraviolet (UV) radiation is a primary environmental risk factor, inducing DNA damage that leads to malignant transformation (Spandidos Publications, 2021). Additional contributing factors include repeated childhood sunburns,

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cumulative UV exposure, atypical moles, chemical exposure, immunosuppression, genetic predisposition, and family history. Epidemiological studies indicate higher susceptibility among older individuals, particularly males.

Melanoma Classification Techniques

Earlier melanoma classification systems relied on traditional machine learning algorithms such as Support Vector Machines (SVM), Random Forests, and K-Nearest Neighbors (KNN). These methods depend heavily on handcrafted features and domain expertise, limiting scalability and Adaptability. In contrast, CNNs automatically learn hierarchical features directly from images, capturing complex spatial patterns. Recent studies demonstrate that CNN-based approaches consistently outperform traditional classifiers in dermoscopic image analysis (Abbas et al., 2023; Yu et al., 2020).

CNNs are composed of convolutional layers for feature extraction, pooling layers for dimensionality reduction, activation functions for non-linearity, and fully connected layers for classification. Techniques such as dropout, batch normalization, and data augmentation are commonly employed to enhance generalization and reduce overfitting (Goodfellow et al., 2016). Well-known architectures such as VGG-16, ResNet-50, and InceptionV3 have shown promising results in skin cancer classification tasks (He et al., 2016).

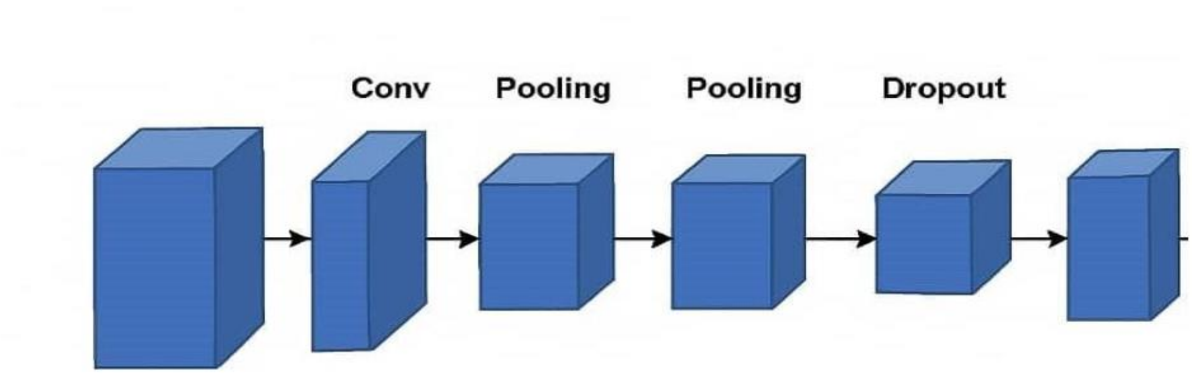
Several recent studies have explored CNN-based and hybrid models for melanoma detection. Musthafa et al. (2024) reported an accuracy of 97.78% using an optimized CNN with extensive data augmentation. DermICNet (2025) introduced attention mechanisms to improve interpretability, though at the cost of increased computational complexity. While these studies demonstrate high performance, challenges related to computational efficiency, interpretability, and dataset diversity remain.

MATERIALS AND METHODS

Dataset and Preprocessing

The HAM10000 dataset, Harvard Dataverse (Tschandl et al., 2018) consisting of 10,015 dermoscopic images labeled as melanoma and non-melanoma, was used in this study (Tschandl et al., 2018). All images were resized to 224× 224 pixels and normalized to a [0,1] range. Data augmentation techniques—including horizontal and vertical flipping, rotation, zooming, and brightness adjustment—were applied to increase dataset diversity and mitigate overfitting.

Figure 1: CNN Architecture



The CNN architecture comprises multiple convolutional layers with ReLU activation for hierarchical feature extraction, followed by max-pooling layers for dimensionality reduction. Dropout layers with a rate of 0.5 were incorporated to prevent over fitting. A soft max output layer was used for binary classification.

Training Parameters:

Optimizer: Adam Learning rate: 0.001

Loss function: Categorical cross-e100 train–test 80/20

Validation strategy: 10-fold cross-validation

Model Evaluation Metrics

The model is evaluated using the following metrics:
Accuracy:

Accuracy = (TP + TN)/ (TP + TN+ FP + FN) ………...1

Precision = TP/ (TP+ FP) …………,…….……….…... 2

Recall =TP/(TP+ FN)…………………………………. 3

F-score = 2 (precision × recall)/(precision + recall) ..… 5
Where:
TP represent True Positive
TN represent True Negative
FP represent False Positive
FN represent False Negative

The performance of the model was evaluated using standard classification metrics, including accuracy, precision, recall, and F1-score, which are widely adopted in medical image Classification studies (Litjens et al., 2017).

RESULTS AND DISCUSSION

Training and Validation Performance

Validation Accuracy (%) Epoch Training Accuracy (%)

Table 1. Training and validation performance across apoch

Epoch	Training Accuracy (%)	Validate (%)
20	88.5	85.7
40	92.4	90.3
60	94.1	92.8
80	96.0	94.2
100	97.2	95.4

The results indicate steady improvement in both training and validation accuracy with decreasing loss values, demonstrating effective learning and minimal over fitting. The just training and validation curves are presented in Figures 3 and 4, respectively.
Figure 2: Training and Validation Accuracy Curve

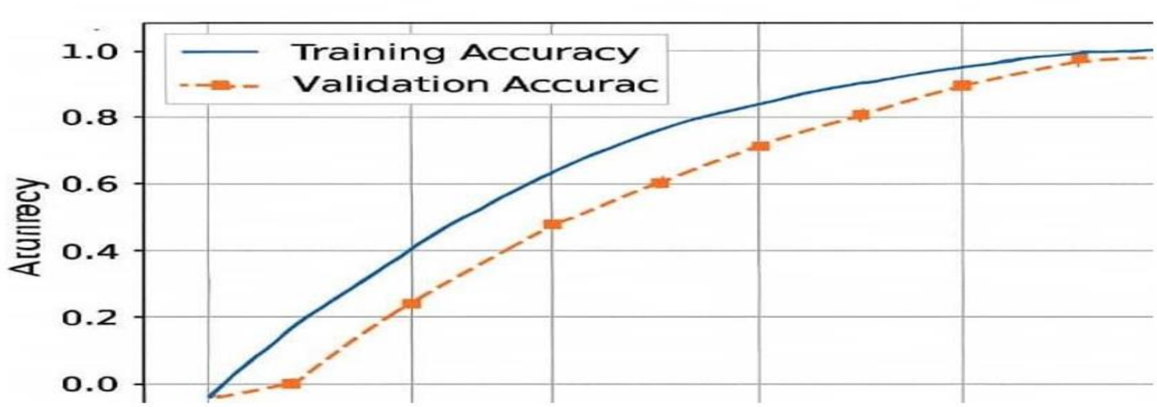
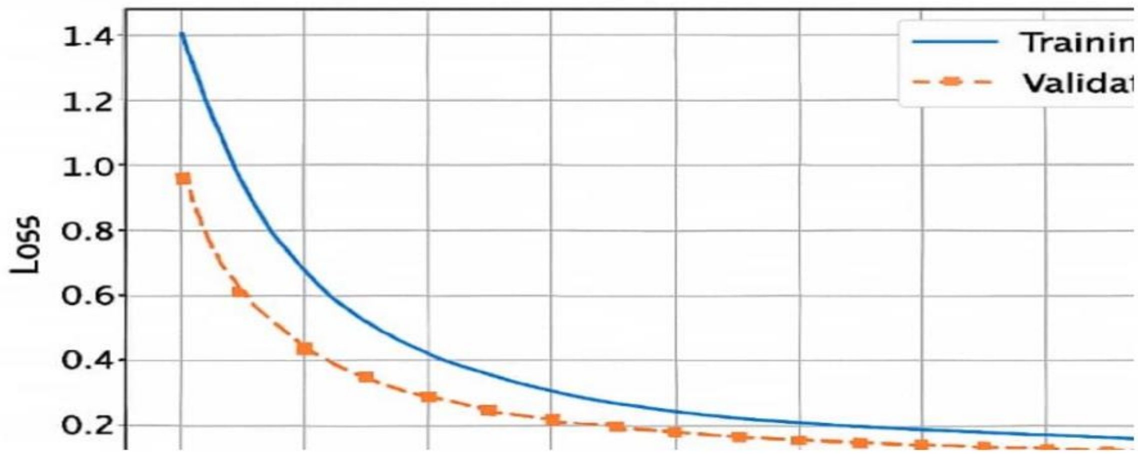


Figure 3: Training and Validation Loss Curve



Confusion Matrix

Predicted Non-Melanoma

The confusion matrix (Table 2) shows high true positive and true negative rates, confirming the reliability and robustness of the proposed model.

Table 2. Confusion Matrix of an enhanced CNN Model

Actual			
	True/Actual Melanoma	480	20
	False/Actual Non-Men-Melanoma	15	485

CONCLUSION

This study presented an enhanced Convolutional Neural Network (CNN) model for automated melanoma skin cancer classification using dermoscopic images from the HAM10000 dataset. The proposed model incorporated comprehensive preprocessing techniques, including image resizing, normalization, and data augmentation, together with an optimized CNN architecture consisting of convolutional, max-pooling, dropout, and Softmax layers. Experimental evaluation demonstrated excellent classification performance, achieving an accuracy of **96.5%**, **96.9% precision**, **96.0% recall**, and an **F1-score of 96.4%**. Furthermore, the confusion matrix results showed **480 correctly classified melanoma images** and **485 correctly classified non-melanoma images**, with only **35 total misclassifications**, confirming the robustness and reliability of the proposed approach.

Compared with traditional machine learning techniques such as Support Vector Machines (SVM), K-Nearest Neighbors (KNN), and Random Forest, which rely heavily on handcrafted feature extraction and expert knowledge, the enhanced CNN automatically learns hierarchical image features directly from dermoscopic images. This capability improves classification accuracy, enhances generalization, reduces overfitting through dropout regularization and data augmentation, and minimizes the need for manual feature engineering. In addition, the proposed model outperformed baseline CNN models and selected pre-trained architectures such as ResNet50 while maintaining relatively low computational complexity, making it suitable for deployment in computer-aided diagnostic systems, particularly in resource-constrained healthcare environments.

Overall, the findings demonstrate that the enhanced CNN provides an accurate, reliable, and efficient solution for early melanoma detection and has significant potential to assist dermatologists in clinical decision-making. Future research should focus on validating the model using larger and more diverse multi-center clinical datasets, improving model interpretability through explainable artificial intelligence (XAI) techniques, and optimizing the model for real-time deployment in clinical practice.

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