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Convolutional Neural Network (CNN) Based Skin Cancer Classification: A Deep Learning Approach

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ABSTRACT

Skin cancer ranks among the most commonly diagnosed forms of cancer worldwide, with millions of new cases identified annually. Over 2 million cases of non-melanoma skin cancer and approximately 132,000 melanoma cases are reported each year . The study aims is to develop an efficient deep learning model using CNN's architectures to accurately classify skin lesions as malignant or benign based on dermoscopic images. This study explored the use of Convolutional Neural Network (CNN) models using AlexNet and ResNet architectures for skin cancer classification. The performance of both models were evaluated based on key metrics such as accuracy, precision, recall, and F1-score. AlexNet was trained on 1,200 skin lesion images and validated on 600 images,training spanned 10 epochs. ResNet was similarly trained and validated after 10 epochs. Both architectures were compared under identical conditions (same dataset, pre-processing, optimizer, and hyperparameters). ResNet outperformed AlexNet in all performance metrics of accuracy as 91.00% and 59.00% respectively. This research explored the performance of CNN(ResNet50) and CNN(AlexNet). This validates that deeper architectures with residual connections, batch normalization, and optimized feature extraction are more effective for binary skin cancer classification.

Keywords: *Convolutional Neural Networks (CNNs),* Residual Network(ResNet50, Adam Optimizer, Computer Vision.

INTRODUCTION

Skin cancer ranks among the most commonly diagnosed forms of cancer worldwide, with millions of new cases identified annually. The World Health Organization (WHO) estimates that over 2 million cases of non-melanoma skin cancer and approximately 132,000 melanoma cases are reported each year (World Health Organization, 2021). While melanoma is less prevalent, it is the most aggressive and deadly form, contributing significantly to skin cancer mortality.According to (Dildar *et al*., 2021), technological progress in deep learning has revolutionized early skin cancer detection by offering noninvasive, efficient, and cost-effective diagnostic approaches.

Recent advancements in artificial intelligence (AI) and deep learning have provided new avenues for addressing these challenges(Naeem *et al*., 2024). Convolutional Neural Networks (CNNs), a class of deep learning models, have demonstrated exceptional capabilities in analyzing medical images, especially in classification of skin lesions. CNNs extract hierarchical features from image data, allowing them to accurately distinguish between benign and malignant lesions, often achieving diagnostic accuracy comparable to experienced dermatologists (Esteva *et al*., 2017). This study leverages CNNs to develop an automated system for skin cancer classification, focusing on enhancing diagnostic accuracy and accessibility.

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Skin disorder poses a significant global health burden, affecting individuals across socioeconomic backgrounds. Beyond their physical symptoms, these conditions can have profound psychological and social effects (Mahfouz *et al.*, 2023).Although AI technologies, especially machine learning and deep learning, offers promising diagnostic solutions, limitations persist. These include limited dataset diversity, model generalizability, and a predominant focus on melanoma.

Moreover, in many rural or underserved regions, the lack of dermatological expertise complicates timely and accurate diagnosis (Dreiseitl *et al.*, 2024). Therefore, there is an urgent need to develop more reliable and accessible AI-based diagnostic tools to address these gaps (Zhang *et al.*, 2023). This research aims to develop an efficient deep learning model using AlexNet and ResNet architectures to accurately classify skin lesions as malignant or benign based on dermoscopic images. Objectives include to collect and preprocess a diverse dataset of labeled dermoscopic skin lesion images and to evaluate and compare the performance of the developed models using key metrics, including accuracy, precision, recall, and F1-score

MATERIALS AND METHODS

Material and method used in developing a efficient deep learning model using Adam optimzer that will optimize Convolutional Neural Network parameters. The methods involve data collection and data acquisition,preprocessing and data augmentation, model creation and optimization to evaluation metrics. The proposed methodology involves utilizing deep learning models specifically AlexNet and ResNet for classifying skin cancer from dermatological images. The methodology followed the CNN structure.

Dataset For The Skin Cancer Classification

CNN Models Training and Evaluation

The training process begins by configuring the model parameters, including the number of epochs, learning rate, and batch size. The dataset, comprising melanoma and non-melanoma images, were preprocessed by resizing all images to 224×224 pixels for ResNet and 227x227 pixels for AlexNet. Augmented datasets have been generated to

The dataset was obtained from kaggle.com website, contains 4000 images of skin cancer. These 4000 images consist of melanoma cancer images and non-melanoma cancer images.

Data Description

The dataset contains two folders for training and testing where each folder contain two sub folders as malignant and belign and each sub folder contained 1000 images.

Data Preprocessing

All images were resized to 224 x 224 pixels for ResNet while for AlexNet were resized to 227 x 227 to match the input requirements of the CNN models. It required to remove artefacts and noise removal to facilitate the segmentation and classification process.

increase variability. The CNN architectures (AlexNet and ResNet) have been initialized, and the networks was trained over the specified number of epochs. Each training iteration have output probability values for classification, with the highest probability indicating the predicted class. The final trained model was saved along with training plots that depict the progress, including loss and accuracy metrics.

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Key training parameters:

i Learning Rate: 0.001 (controls the speed at which the model learns)

Batch Size: 32 (chosen based on available memory to optimize processing)
Epoch:10

Performance Evaluation Metrics

Evaluation metrics used include the confusion matrix, accuracy, precision, recall, F1-score, and ROC-AUC. Given true positives (TP), false positives (FP), true negatives (TN), and false negatives (FN), these measures are calculated as follows:

$$\text{Accuracy} = \frac{TP+TN}{TP+FP+TN+FN} \quad (1)$$

$$\text{Precision} = \frac{TP}{TP+FP} \quad (2)$$

$$\text{Recall} = \frac{TP}{TP+TN} \quad (3)$$

$$\text{F1Score} = \frac{2*\text{Precision}*\text{Recall}}{\text{Precision}*\text{Recall}} \quad (4)$$

RESULTS AND DISCUSSION

This secpresents the experimental results obtained from implementing the proposed Convolutional Neural Network (CNN) models using AlexNet and ResNet architectures for skin cancer classification. The performance of both models were evaluated based on key metrics such as accuracy, precision, recall, and F1-score. The outcomes are discussed in the context of related works and the study's objectives. Python Programming environment combined with TesnsorFlow and matplot libraries for integrating advanced CNN models along with Adam Optimizer were used for the implementation.

Result Analysis

AlexNet Architecture Results
AlexNet was trained on 1,200 skin lesion images and validated on 600 images. Training spanned 10 epochs and achieved a validation accuracy of 59.00%.

Table 1: Confusion Matrix AlexNet

	Predicted Benign	**Predicted Malignant**
Actual Benign	96	204
Actual Malig	42	258

Table 2: AlexNet Classification Result

	Precision	**recall**	**f1-score**	**support**
benign	0.7	0.32	0.44	300
malignant	0.56	0.86	0.68	300
accuracy			0.59	
macro avg	0.63	0.59	0.56	600
weighted avg	0.63	0.59	0.56	600

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Figure 1: Model Accuracy Chart at Training Time of the AlexNet Architecture

ResNet Architecture Results

ResNet was similarly trained and validated with improved performance, reaching a maximum validation accuracy of 91% after 10 epochs.

Table 3: Confusion Matrix for ResNet50.

	Predicted Benign	Predicted Malignant
Actual Benign	274	26
Actual Malig.	272	28

Table 4: Classification Report of ResNet50.

	Precision	recall	f1-score	support
benign	0.91	0.91	0.91	300
malignant	0.90	0.90	0.90	300
accuracy			0.91	
macro avg	0.91	0.91	0.91	600
weighted avg	0.91	0.91	0.91	600

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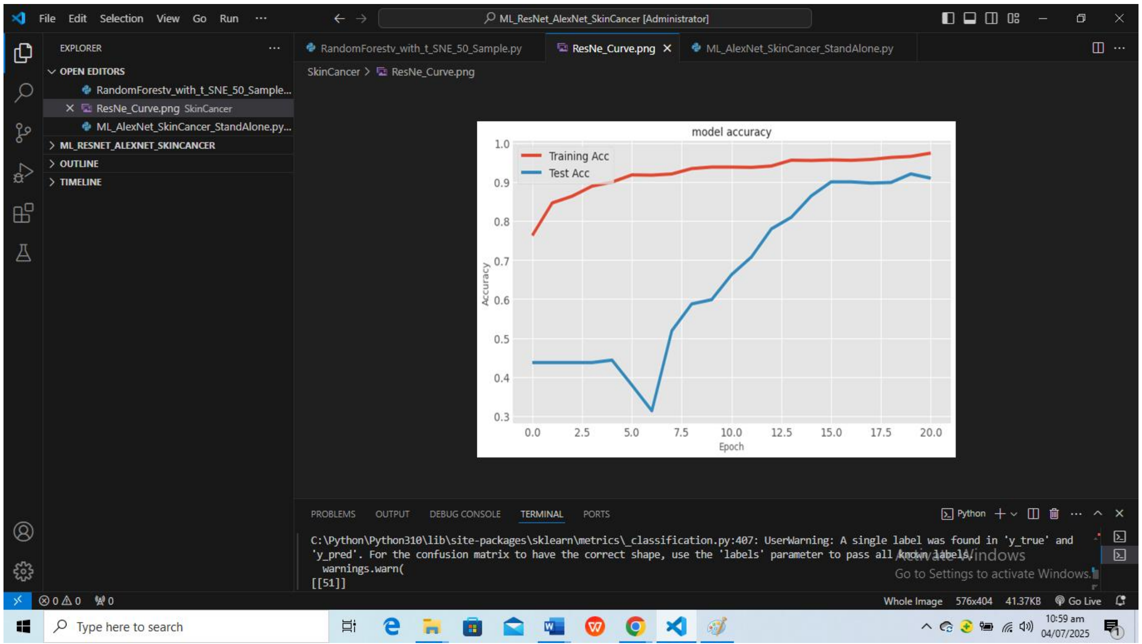

Figure 2: Model Accuracy Chart at Training Time of ResNet Architecture

Comparative Analysis

Both architectures were compared under identical conditions (same dataset, pre-processing, optimizer, and hyperparameters). ResNet outperformed AlexNet in all performance metrics of accuracy as 91.00% and 59.00% respectively.

DISCUSSION

This research explored the performance of CNN(ResNet50) and CNN(AlexNet) where ResNet 50 outperforms AlexNet in image classification due to its deeper architecture and residual connections which enable better future extraction and mitigate vanishing gradients. However, the ResNet50 architecture is computational more expensive than AlexNet due to its increased dept, but its improved accuracy make it more a popular choice for machine learning model applications.

This validates that deeper architectures with residual connections, batch normalization, and optimized feature extraction such as ResNet 50 are more effective for binary skin cancer classification. These results reinforce the findings in related literature and demonstrate the robustness of the proposed hybrid CNN framework. Overall, the study demonstrates that advanced machine learning techniques, specifically the integration of CNN and ResNet50, can significantly enhance early prediction models, offering valuable tools in medical field sector to improve early detection and diagnosis.

CONCLUSION

The study concluded that deep learning models, particularly those based on residual networks like ResNet, offer significant potential in automating skin cancer diagnosis from dermoscopic images. ResNet's superior performance can be attributed to its ability to train deeper layers effectively through skip connections, enabling it to capture more complex visual features.

To further advance the utility and clinical applicability of the proposed models, future research should focus on integrating explainable artificial intelligence (XAI) techniques,which will be essential in enhancing transparency, allowing clinicians to interpret and trust the model's predictions by highlighting which parts of the skin lesion image contributed most to the classification decision.

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