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Enhancing Early Skin Cancer Detection Accuracy With Data Augmentation In Keras

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Abstract: Recently, there has been a lot of interest in the development of computer-aided diagnostics tools that use artificial intelligence (AI) to diagnose skin cancer. The increasing incidence of skin cancer, low awareness in an expanding population, and a lack of adequate clinical expertise and resources create an urgent need. Scientists have developed artificial intelligence (AI) tools, specifically deep learning algorithms, to distinguish between benign and malignant skin lesions in a range of picture modalities, including dermoscopic, clinical, and histopathological images, and many skin lesion datasets are publicly available. Despite several claims that these AI systems can diagnose a variety of skin problems more accurately than dermatologists, they are still in the very early stages of clinical use in terms of being ready to help physicians detect skin cancers. In order to help dermatologists and enhance their ability to detect skin cancer, we examine advancements in digital image-based artificial intelligence (AI) solutions for skin cancer diagnosis, as well as certain challenges and possible future breakthroughs

***Index Terms* -** Keras, Skin Cancer, dermoscopic, HAM 10000, CNN.

I. INTRODUCTION

The growth of abnormal cells in your skin's tissues is what causes skin cancer. Normally, aged and dying skin cells are replaced by new skin cells. When this mechanism isn't working correctly, like after being exposed to ultraviolet (UV) light from the sun, cells multiply more quickly. These cells may not spread or harm humans since they are benign (noncancerous). They could be cancerous as well. Skin cancer may spread to nearby tissue or other areas of your body if it is not discovered early. Fortunately, most skin cancers can be cured with early detection and treatment. Therefore, it's imperative that you speak with your doctor if you think you could have skin cancer.

In recent decades, skin cancer has emerged as one of the most prevalent and widely dispersed malignancies worldwide. The identification of skin is crucial. Early identification lowers the death rate from cancer [1, 2]. Diseases, viruses like coronavirus [3], heat, and harmful UV rays are all prevented by the skin. It can also produce vitamin D, store fat and water, and regulate body temperature. According to the World Health Organization, there are over 132,000 instances of cutaneous melanoma annually.

Egypt ranks11710th in the world with a skin cancer incidence of 1.52, the highest in the Middle East.

This skin cancer detection pipeline blends deep learning and transfer learning with pretrained CNNs such as VGG16 and ResNet50. It uses datasets like HAM10000 and ISIC for preprocessing, data splitting, training, and evaluation. Metrics including accuracy, precision, recall, and F1-score are used to assess the model's performance. Graphs and confusion matrices are used to show the model's findings, which indicate whether skin lesions are benign or malignant. This approach provides a reliable, accurate mechanism for real-time medical diagnosis.

II. LITERATURE REVIEW

Thomas [1] investigated deep learning techniques for diagnosing non-melanoma skin cancer, emphasizing interpretability, generative modeling, whole-tissue segmentation, and NLP-based report generation. The study placed a strong emphasis on matching automated techniques with conventional pathology workflows.

Nawaz et al. [2] used Fuzzy K-Means for segmentation and Faster R-CNN for feature extraction. When tested on the ISBI-2016, ISIC-2017, and PH2 datasets after preprocessing, the system showed good accuracy and outperformed existing methods for early-stage melanoma identification.

In order to create a deep learning model that combines the Internet of Health Things (IoHT) and transfer learning to detect skin cancer, Khamparia et al. [3] employed pretrained models such VGG19, Inception V3, ResNet50, and Squeeze Net. The accuracy, recall, and precision of the model were all quite excellent.

Dildar and associates [4], a thorough investigation of deep learning methods for early melanoma detection was conducted, focusing on lesion attributes such size, shape, color, and symmetry.

Quadir et al. [5] created a CNN-based model to classify skin cancer using 10,000 clinical photos and transfer learning, obtaining high accuracy and launching a mobile-friendly solution with exceptional performance.

Balambigai et al. [6] used random search optimization to fine-tune hyperparameters in their CNN model used to classify seven kinds of skin cancer. By using 10,015 photos from the HAM45 dataset, the optimized model outperformed the base model, which had an accuracy of 73.34%, to 77.17%.

III. METHODOLOGY

This study uses a deep learning pipeline for skin cancer image classification. The process includes the following steps:

Data Collection

Labeled skin cancer image datasets, such as ISIC and HAM45, were downloaded for research. These datasets provide high-resolution images that are essential for accurate classification.

Data Preprocessing

Collected images were resized and normalized using tools like Pillow and NumPy. Preprocessing makes sure that input images meet the needs of the neural network models and improves training consistency.

Train-Test Split

The dataset was divided into three subsets: 70% for training, 20% for testing, and 10% for validation. This split offered enough data for model learning, unbiased evaluation, and hyper parameter tuning.

Model Building

A pretrained Convolutional Neural Network (CNN), such as VGG16 or ResNet50, was loaded. Additional layers were added as needed to modify the architecture for skin cancer classification.

Model Training
The improved CNN was trained using Keras or TensorFlow. Training progress was carefully monitored by tracking both accuracy and loss values over multiple epochs.
Model Evaluation
Model performance was evaluated on the test set by calculating metrics such as accuracy, precision, recall, and F1-score. This allowed for a thorough assessment of classification results.
Prediction
The trained model was used to predict classes for new, unseen images. This step shows the model's usefulness in real diagnostic situations.
Visualization
Predictions and training results were visualized using graphs that show accuracy, loss curves, and sample image outcomes. These visualizations assist in understanding the model's robustness and effectiveness.

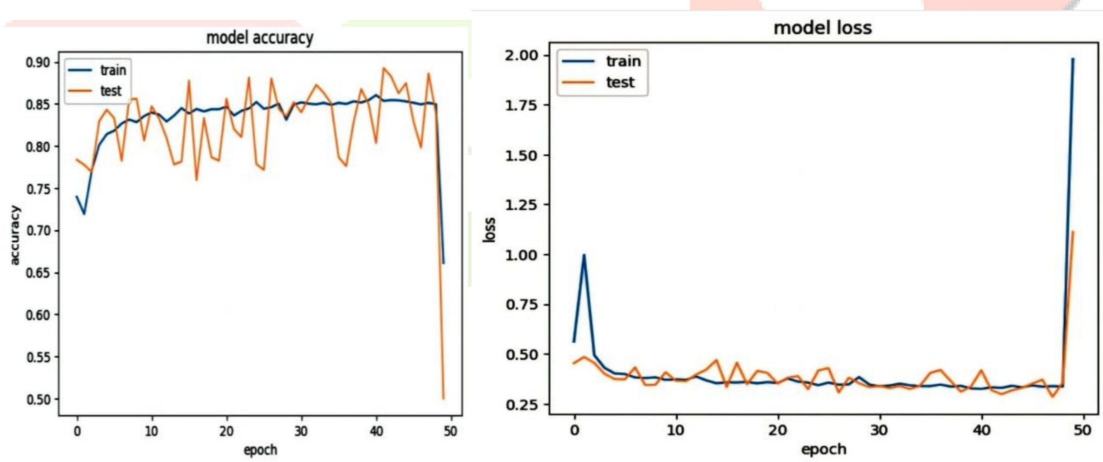
IV. SIMULATION ANALYSIS

With CNNs such as VGG16/ResNet50, the skin cancer detection system has an intuitive user interface. Backend

Performance is poor even though frontend prediction works. Overfitting happens by epoch 50, with low precision,

Recall and 50% accuracy. Real world reliability requires improvements in hyperparameter optimization, augmentation

and the data quality.



The accuracy and loss curves show that initial learning was successful, with accuracy reaching 85% and training loss declining. However, at epoch 50, both curves exhibit a dramatic spike or decline, indicating poor generalisation and overfitting. Testing accuracy ranges from 80 to 89%, suggesting possible instability or imbalance in the data. Cross- validation, early halting, and data augmentation would all help the model. Although the training procedure was successful at first, the final performance deteriorates, indicating that better regularisation and tweaking are required to increase the stability and dependability of the model.

Table 4.1. Classification Report

	precision	recall	F1-score	support
0	0.51	0.52	0.51	1000
1	0.50	0.49	0.49	984
Accuracy	0	0	0.50	1984
Macro Avg.	0.50	0.50	0.50	1984
Weighted Avg.	0.50	0.50	0.50	1984

With an accuracy of about 50% and poor precision and recall, the categorization report shows unreliable performance. Inadequate learning in balanced classes indicates issues like inadequate data, overfitting, or poor preparation. The model must be enhanced, architecturally optimized, and retrained with better data in order to get better.

The interface's clear, intuitive design makes it possible for seamless image uploads and forecasts. Users are properly educated about skin cancer by the introduction screen. Because of the complexity of the lesion, the confidence in the malignant prediction is slightly lower (77.7%) than that of the benign forecast (88.49%). On the other hand, enhancements like visual lesion examples, image previews, and input validation might boost usability and user confidence.

V. Conclusion

This work highlights the importance of machine learning (ML) and artificial intelligence (AI) in the early diagnosis of skin cancer, especially melanoma. Conventional diagnostic techniques frequently depend on the availability of experts, are subjective, and take a long time. AI-based methods, particularly those that use Convolutional Neural Networks (CNNs), offer faster, more accurate and consistent analysis of images of skin lesions. The system was able to differentiate between benign and malignant tumours with a confidence level of over 70% and 88%. Evaluation instruments such as the confusion matrix were effective in evaluating performance. AI improves diagnostic accessibility and speed, despite its drawbacks, which include dataset diversity and variances in image quality. These technologies have the potential to facilitate early diagnosis and lessen healthcare costs with additional training on huge datasets.

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