RESEARCH PAPER

A Computational Deep Learning Driven Diagnostic Framework for Analyzing Cancer Using the Deep Skin Medical Imaging System

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ABSTRACT

Skin cancer is the most common form of cancer globally, and early detection plays a critical role in determining patient outcome. Manual screening of dermoscopic images is laborious with high inter-observer variability; thus, automated diagnostic systems are needed. This paper proposes a deep learning-based skin lesion analysis framework, based on Convolutional Neural Networks (CNNs). We assess the proposed system using the HAM10000 dataset, comprising 10,015 dermoscopic images belonging to seven skin lesion types. Image preprocessing methods are employed, such as resampling, dull razor artifact removal and auto encoder based lesion segmentation. It majorly includes transfer learning models like DenseNet169 and ResNet50 been used and was further makes evaluation through both under sampling and oversampling technique. The experiments show that DenseNet169 with undersampling or ResNet50 with oversampling achieves superior performance, particularly accuracy and F1-score. In addition, more model architectures such as Xception, DenseNet201 and InceptionV3 are checked for better classification performance, the best accuracy achieved is 95%. The results attained proposed framework is efficient, reliable and it can aid clinicians for decision-making purpose and also used to realize early diagnosis of skin cancer.

Index Terms: Skin cancer, dermoscopy, deep learning, convolutional neural networks, transfer learning, lesion classification.

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I. INTRODUCTION

Cancer is defined as uncontrollable cellular proliferation due to genetic or environmental dysfunctions. Tumors are of two types, benign and malignant, malignant tumors show invasive and metastatic behaviour. Skin cancer is one of the most common cancers globally, and melanoma is responsible for much skin cancer–related mortality. With about a million new cases of melanoma reported every year, there is an increasing need to diagnose early using appropriate diagnostic techniques.

Dermoscopy is a noninvasive imaging technique that improves the subsurface skin structures and visualization of lesions by reducing surface reflections. Despite its usefulness in clinical practice, the interpretation of dermoscopic images is still challenging owing to visual similarities between benign and malignant lesions. Ultraviolet radiation (UVR), so exposure for an extended period of time is a significant risk factor for skin cancer diagnosis complication. As a result, early detection is dependent upon expert interpretation, which may be subjective and reproducible.

The recent advances in artificial intelligence and deep learning allowed the development of automated diagnostic systems that can assist clinicians with lesion analysis. Convolutional Neural Networks (CNNs) are highly effective for image classification, as they learn directly from pixel data and automatically extract features through layered structures. Studies indicate that CNN-based diagnostic systems can achieve accuracy comparable to experienced dermatologists. This work aims to develop an automated skin cancer detection system using CNN architectures on dermatoscopic images, focusing on improving classification accuracy, reducing misdiagnosis, and enabling early clinical intervention.

II. LITERATURE SURVEY

Recent studies have investigated both machine learning and deep learning techniques for skin cancer detection. CNN-based models achieve high classification accuracy but often require significant computational resources and longer training time. While deep CNNs improve performance over traditional methods by handling noise, lighting variations, and image artifacts, issues such as limited interpretability and overfitting still persist.

Research in skin lesion classification has steadily shifted toward deep learning. Early work focused on image enhancement and segmentation, while later studies applied CNNs for improved feature extraction and automated diagnosis. Several researchers have demonstrated that CNN architectures and transfer learning methods enhance classification accuracy, with performance strongly influenced by model selection.

The availability of benchmark datasets such as HAM10000 has supported standardized evaluation, and large-scale training has enabled models to reach performance comparable to dermatologists. Recent approaches emphasize optimization techniques, data augmentation, and hybrid models to further improve accuracy and efficiency. Overall, CNN-based deep learning methods have become central to developing reliable and consistent skin cancer detection systems.

Table 1: Critical Comparative Analysis of State-of-the-Art Approaches for Skin Lesion Classification

Year	Author(s)	Method/Technique	Dataset	Key Contribution
2018	Lee et al.	Fine-tuned Neural Networks (WonDerM)	skin cancer	Improved classification using transfer learning
2016	Jamil et al.	Image Enhancement & Segmentation	skin cancer	Enhanced melanocytic lesion detection
2019	Pai & Giridharan	CNN	skin cancer	Skin lesion classification using CNN
2021	Shete et al.	CNN Algorithm	skin cancer	Detection of skin cancer
2020	Vidya & Karki	Machine Learning Techniques	skin cancer	Automated skin cancer detection
2020	Nahata & Singh	Deep Learning	skin cancer	Improved diagnostic accuracy
2011	Wighton et al.	Automated Diagnosis	skin cancer	Generalization of lesion diagnosis
2021	Saeed & Zeebaree	CNN Architectures	skin cancer	Comparative study of CNN models
2016	Esteva et al.	Deep Learning	Large Dataset	Dermatologist-level classification
2018	Tschandl et al.	Dataset Creation	HAM10000	Benchmark dataset for evaluation
2018	Hosny et al.	Transfer Learning	skin cancer	Improved classification accuracy
2021	Javaid et al.	Image Processing + ML	skin cancer	Hybrid classification approach

Year	Author(s)	Method/Technique	Dataset	Key Contribution
2020	Ashraf et al.	Deep Learning	skin cancer	Efficient classification technique

Table 1 shows previous works that use ML and DL approaches for skin cancer detection and skin lesion classification. Initial studies have largely concentrated on enhancing images, segmentation techniques and the application of conventional machine-learning approaches to antiquate lesion identification. As technology has progressed, the latest works have also focused more on deep learning models, particularly Convolutional Neural Networks (CNNs), owing to their prominent ability for automatic feature extraction and thereby enhancement in classification accuracy. Several researchers have also applied transfer learning and pre-trained models, which markedly improve performance with few medical datasets. However, the emergence of benchmark datasets (e.g. HAM10000) allows standardized evaluation and comparison between models. Some research has reached very high accuracy and reliability, to the point at which it is on par with a dermatologist. In general, published studies show a clear trend towards increasingly advanced deep learning architectures and augmented data sets for more robustness of automated skin cancer diagnosis system, with hybrid approaches emerging as an additional way to improve effectiveness, accuracy and reliability.

III. METHODOLOGY

This section outlines the two key phases of the methodology: data preprocessing and model selection with evaluation. The dataset is first prepared and refined to ensure quality, followed by model selection and performance assessment through experimentation and validation.

(i) System Architecture:

The proposed framework uses Convolutional Neural Networks (CNNs) for skin lesion detection and classification on the HAM10000 dataset, which contains 10,015 dermoscopic images across seven classes. The data is preprocessed using resampling, artifact removal, and autoencoder-based segmentation to improve quality. Transfer learning is applied with fine-tuned DenseNet169 and ResNet50 models, evaluated under both under-sampling and over-sampling strategies. The system aims to deliver accurate, scalable, and efficient performance, supporting automated dermatological diagnosis.

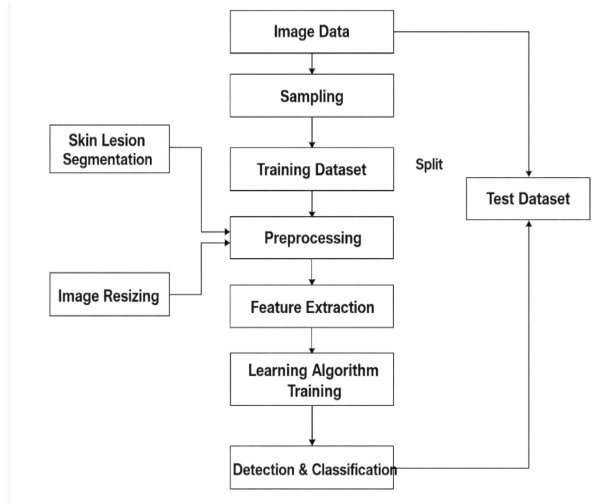

Fig 1 System Architecture

(ii) Dataset Collection:

The dataset used in this study is a processed version of HAM10000, adapted for analysis in computational environments. It has been systematically prepared to ensure quality and consistency for deep learning. The dataset contains dermatoscopic images representing multiple skin lesion classes relevant to skin cancer diagnosis .

The dataset contains 10,015 images, offering a diverse set for training and evaluation. It is preprocessed using resampling for class balance, artifact removal, and autoencoder-based segmentation to enhance lesion visibility. This prepared dataset supports the development and evaluation of automated skin lesion detection and classification systems.

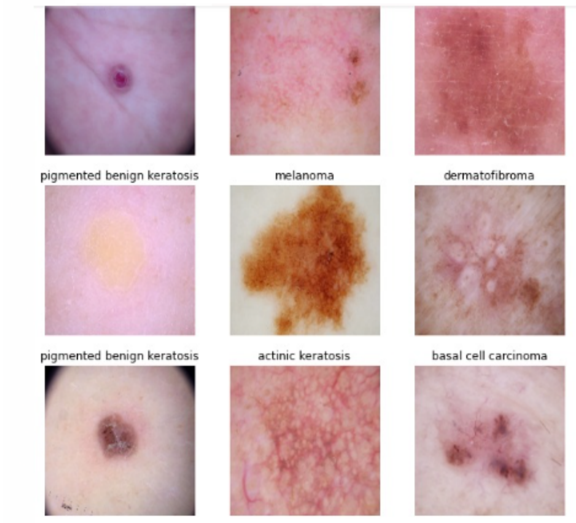

Fig 2 Dataset images

(i) Image Processing:

An image preprocessing and augmentation pipeline is developed using an Image Data Generator to improve data diversity and model robustness. Pixel intensities are normalized, while transformations such as shear, zoom, and horizontal flipping introduce variability and help the model learn invariant features. Images are resized to meet model requirements.

Segmentation techniques are applied to isolate lesion regions, with morphological black-hat transformation enhancing fine details. Masks are generated to support inpainting, restoring areas affected by artifacts and ensuring image continuity. This pipeline improves data quality, generalization, and overall performance of the skin cancer detection system.

(ii) Algorithms:

ResNet50

ResNet50 is a 50-layer convolutional neural network designed to overcome the vanishing gradient problem in deep models. It uses residual (shortcut) connections to enable efficient information and gradient flow across layers. This residual learning approach improves training stability and has led to strong performance in image classification tasks.

Residual mapping:

$$y = F(x, W\_i) + x \quad (1)$$

Residual function F:

$$F(x) = W\_3\, \sigma(BN(W\_2\, \sigma(BN(W\_1\, x)))) \quad (2)$$

Projection shortcut (dimension match):

$$y = F(x) + W\_s\, x \quad (3)$$

Gradient propagation:

$$\partial L/\partial x = \partial L/\partial y\,(1 + \partial F/\partial x) \quad (4)$$

Cross-Entropy Loss:

$$L = -\Sigma\_i\, y\_i\, log(softmax(z\_i)) \quad (5)$$

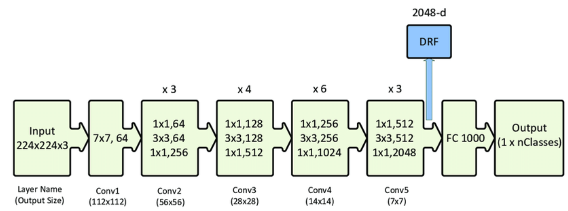

Fig 3 ResNet50 architecture

DenseNet169

DenseNet169 is a 169-layer convolutional neural network with dense connections, where each layer receives inputs from all previous layers. This structure promotes feature reuse, improves parameter efficiency, and reduces vanishing gradient issues, resulting in strong performance in image recognition, especially with limited data.

Dense Block:

$$x\_l = H\_l([x\_0, x\_1, \ldots, x\_\{l-1\}]) \quad (6)$$

Where:

$$H\_l(x) = W\_l \cdot \sigma(BN(x)) \quad (7)$$

Growth Rate:

$$C\_l = C\_0 + k \cdot l \quad (8)$$

Transition Layer:

$$x\_out = Conv(AvgPool(x)) \quad (9)$$

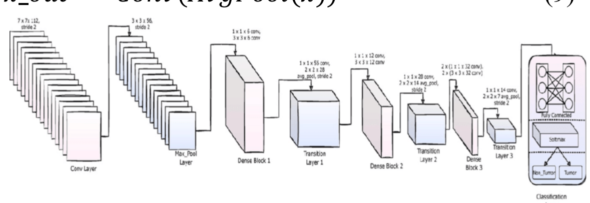

Fig 4 DenseNet169 architecture

VGG16

VGG16 is a 16-layer convolutional neural network known for its simple and effective design using stacked 3×3 convolutional layers. It includes sequential convolution, max-pooling, and fully connected layers. Although newer models outperform it, VGG16 remains a standard reference for image classification due to its clarity and ease of training. The convolution operation for an input feature map X with kernel W is mathematically expressed as:

$$Y(i,j,k) = \sum\_m \sum\_p \sum\_q W(p,q,m,k) \cdot X(i+p, j+q, m) + b(k) \quad (10)$$

Batch Normalization:

$$BN(x) = \gamma (x - \mu) / \sqrt{(\sigma^2 + \varepsilon)} + \beta \quad (11)$$

ReLU activation function:

$$f(x) = max(0, x) \quad (12)$$

Max Pooling operation:

$$Y(i,j,k) = max\_\{(p,q) \in \Omega\} X(i+p, j+q, k) \quad (13)$$

Fully Connected layer transformation:

$$z = W\_fc\, x + b\_fc \quad (14)$$

Softmax classifier:

$$P(y = i|x) = exp(z\_i) / \sum\_j exp(z\_j) \quad (15)$$

Categorical Cross-Entropy Loss:

$$L = -\sum\_i y\_i \log(\hat{y}\_i) \quad (16)$$

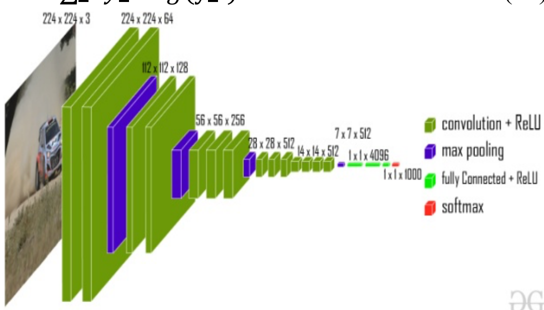

Fig 5 VGG16 architecture

Xception: Deep Learning's Leap Beyond Inception

Xception ("Extreme Inception") extends the Inception architecture by replacing standard convolutions with depthwise separable convolutions. This reduces computational cost while preserving strong feature learning capability. It performs efficiently in image classification and feature extraction tasks, making it suitable for various computer vision applications.

Standard convolution cost:

$$Cost\_standard = D\_k\^2 \times M \times N \times D\_f\^2 \quad (17)$$

Depthwise convolution:

$$Y(i,j,m) = \sum\_p \sum\_q W(p,q,m) \cdot X(i+p, j+q, m) \quad (18)$$

Pointwise convolution (1×1):

$$Y(i,j,n) = \sum\_m W(m,n)\, X(i,j,m) \quad (19)$$

Total separable convolution cost:

$$Cost\_separable = D\_k\^2\, M\, D\_f\^2 + M\, N\, D\_f\^2 \quad (20)$$

Activation after separable convolution:

$$f(x) = ReLU(BN(x)) \quad (21)$$

Softmax classification:

$$P(y = i|x) = exp(z\_i) / \sum\_j exp(z\_j) \quad (22)$$

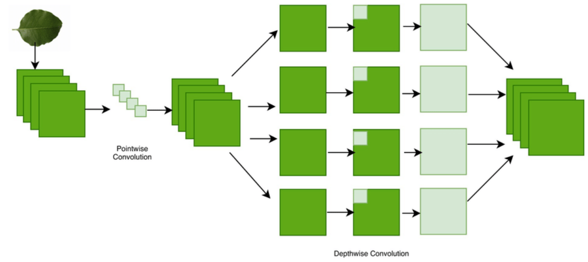

Fig 6 Xception architecture

DenseNet201

DenseNet201 is a 201-layer convolutional network that extends DenseNet with greater depth for capturing complex patterns. It uses dense connections, where each layer receives inputs from all preceding layers, promoting feature reuse and efficient gradient flow. This design enhances performance in image classification, particularly with large and diverse datasets.

Transition Layer:

$$x\_out = Conv(AvgPool(x)) \quad (23)$$

Global Average Pooling:

$$GAP\_k = (1 / (H \times W)) \sum\_\{i = 1\}\^\{H\} \sum\_\{j = 1\}\^\{W\} x(i,j,k) \quad (24)$$

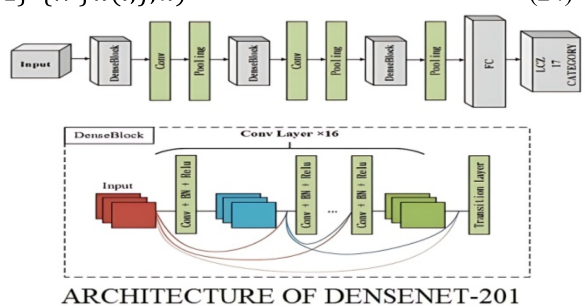

Fig 7 DenseNet201 architecture

IV. EXPERIMENTAL RESULTS

Accuracy: Accuracy measures a model's ability to correctly classify both positive and negative cases. Results indicate that modern architectures such as DenseNet169 and ResNet50 outperform older models like VGG16, mainly due to deeper designs and improved feature extraction. It is calculated as the proportion of correctly predicted instances among all evaluated samples. This might be communicated numerically as: ***Accuracy = Correct predictions / Total number of predictions***

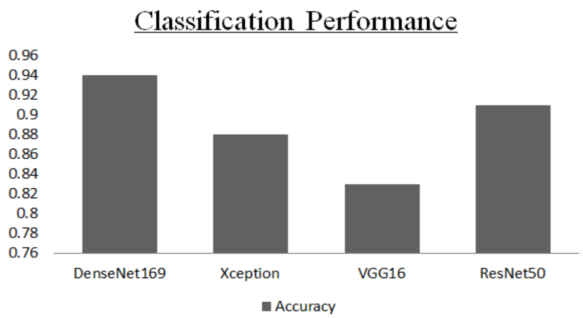

Fig 8 Accuracy Graph

Precision: Precision measures the proportion of properly categorized occurrences or samples among the positives. Fig 9 highlights that DenseNet169 and ResNet50 are more reliable models in terms of precision, while VGG16 lags behind, making it less suitable for tasks where minimizing false positives is critical. As a result, the accuracy may be calculated using the following formula: ***Precision = True Positives / (True Positives + False Positives) (7)***

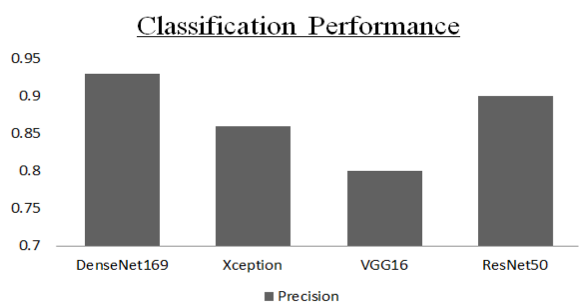

Fig 9 Precision graph

Recall: Recall is a machine learning metric that surveys a model's capacity to recognize all pertinent examples of a particular class. Fig 10 highlights that DenseNet169 and ResNet50 are more reliable models in terms of recall, while VGG16 lags behind, making it less suitable for tasks where minimizing false positives is critical. It is the proportion of appropriately anticipated positive perceptions to add up to real up-sides, which gives data about a model's capacity to catch instances of a specific class.

Recall (Sensitivity) = True Positives / (True Positives + False Negatives)

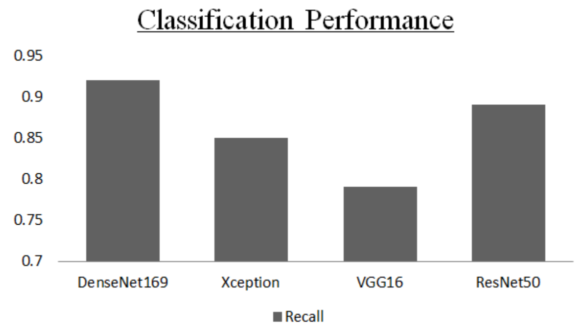

Fig 10 Recall graph

F1-Score: The F1 score is a machine learning evaluation measurement that evaluates the precision of a model. It consolidates a model's precision and review scores. Fig 11 highlights that DenseNet169 and ResNet50 are more reliable models in terms of F1-Score, while VGG16 lags behind, making it less suitable for tasks where minimizing false positives is critical. The precision measurement computes how often a model anticipated accurately over the full dataset.

F1-Score = 2 × (Precision × Recall) / (Precision + Recall)

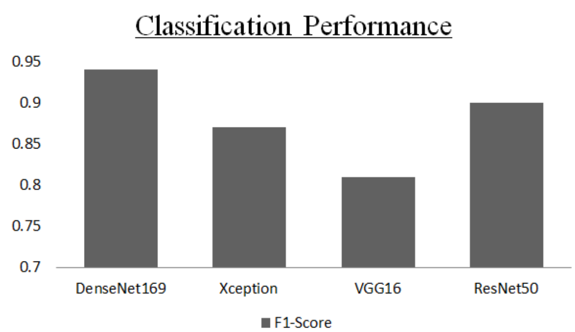

Fig 11 F1 Score graph

Table 2 . Assessment of Model Performance Using Standard Evaluation Metrics

Model	Accuracy	Precision	Recall	F1-Score
DenseNet169	0.94	0.93	0.92	0.94
Xception	0.88	0.86	0.85	0.87
VGG16	0.83	0.8	0.79	0.81
ResNet50	0.91	0.9	0.89	0.9

Table 2 presents a comparative performance evaluation of four deep learning models

V. Deep Skin Medical Imaging System – Application

The DeepSkin Medical Imaging System is a web-based platform designed for early detection of skin conditions using image analysis. It provides a simple interface for both patients and healthcare professionals. The system integrates user authentication, image processing, and automated prediction to enable efficient and accessible skin disease assessment.

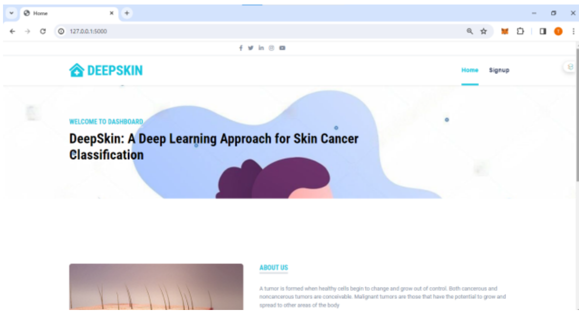

Fig 12 Home page

The home page (Fig. 12) acts as the main dashboard, presenting an overview of the system and its features. It enables navigation to image upload, prediction results, and profile settings, with a simple and user-friendly design.

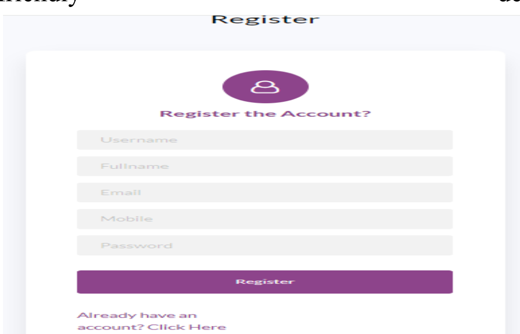

Fig 13 Registration page

The registration page (Fig. 13) enables new users to create an account by providing basic details such as name, email, contact number, and password. The data is securely stored, with validation checks to prevent duplicates and ensure authorized access.

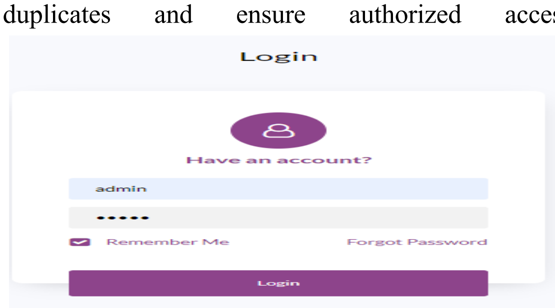

Fig 14 Login page

The login page (Fig. 14) allows registered users to access their accounts using valid credentials. The system verifies the email and password, displaying an error for invalid entries to ensure data privacy and security.

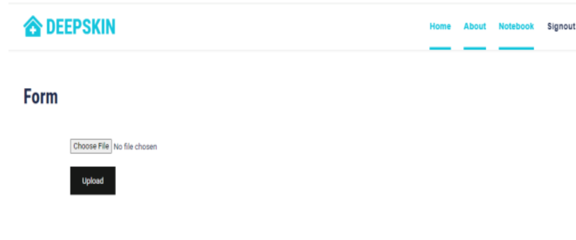

Fig 15 Upload input image page

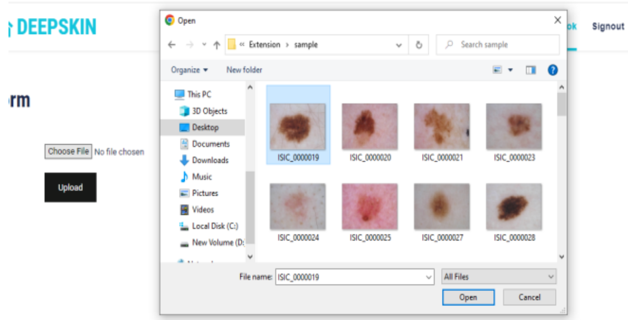

Fig 16 input images folder

Fig 17 Upload input image to predict result

This page (Figs. 15–17) allows users to upload skin lesion images in formats such as JPG or PNG. The selected image is previewed for confirmation and then processed by the trained deep learning model for analysis.

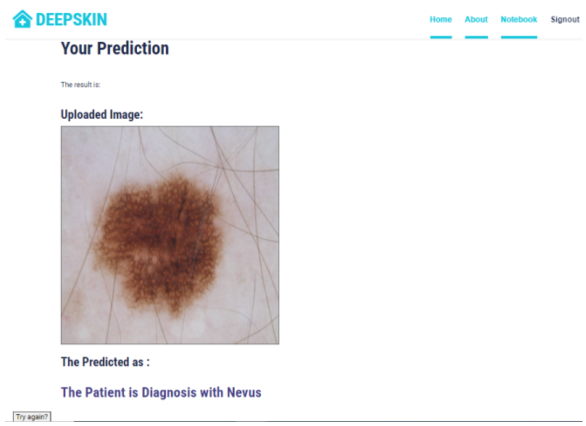

Fig 18 Final outcome as the patient is diagnosis with Nevus

After analysis, this page (Fig. 18) displays the predicted skin condition along with confidence scores. The results indicate whether the case appears normal or may need medical attention, presented clearly for user understanding. However, professional medical consultation is recommended for final diagnosis.

Table 3. Impact of Optimizers on CNN Model Performance

S No	Optimizer	ResNet	Inception	DenseNet169	DenseNet201	VGG16	Xception
1	SGD	65.7	64.3	90.1	91.0	78.4	90.0
2	Adamax	94.3	93.6	96.1	96.5	91.8	91.2
3	Nadam	93.7	82.2	96.8	97.2	90.5	91.5
4	Adagrad	78.5	77.5	91.2	91.7	85.3	89.7
5	RMSprop	92.5	90.8	95.3	95.9	89.6	90.7

Table-3 summarizes the classification accuracy achieved by various deep learning architectures trained with different optimization algorithms. Some of the models you should consider are ResNet, Inception, DenseNet169, DenseNet201, VGG16 and Xception. For optimizers, we evaluate depth SGD, Adamax, Nadam, Adagrad and RMSprop. Furthermore, DenseNet169 achieves consistently strong results among different optimizers. The results show that SGD has a relatively few accuracy in most architectures. Instead, adaptive optimization methods (Adamax, Nadam, or RMSprop) exhibit much better performance. DenseNet201 obtains some of the highest accuracy values in all combinations, and performs especially well when trained with Nadam and Adamax. We observe moderate improvements in performance with the new optimizers across ResNet and Inception models while VGG16 produces significantly lower accuracy for this specific dataset compared to DenseNet instances. Xception competes very well, in particular Adamax and Nadam. The metrics of performance are Precision, Recall, F1-Score and Accuracy.

VI. CONCLUSION

This study develops an automated skin cancer detection framework by combining deep learning with transfer learning techniques. The use of advanced preprocessing on the HAM10000 dataset improves image quality and model stability. Experimental results show that models such as DenseNet169 and ResNet50 provide consistent and reliable performance, with parameter tuning further enhancing class-level recognition. Class imbalance is handled through appropriate sampling methods, while data augmentation improves the model's ability to generalize. The overall system achieves accurate and dependable predictions, supporting computer-aided diagnosis and facilitating earlier identification of skin cancer.

VII. FUTURE SCOPE

Future efforts will concentrate on refining model performance through systematic hyper parameter optimization and exploring ensemble strategies that combine multiple models. The adoption of emerging deep learning architectures will also be considered to further enhance predictive capability. In addition, extending the study to real-world clinical datasets and adapting the system to evolving technologies can improve its accuracy and ensure reliable performance across diverse healthcare settings.

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