

AI Based Skin Cancer Detection

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ABSTRACT

Intelligent skin cancer detection using a balanced collection of photos of various cancer skin moles is the main focus of this study. One common kind of cancer that forms improperly on skin cells is skin cancer. Studies have shown that skin cancer survival rates are much higher when detected early. Basal cell carcinoma, and nevus are the main types of skin cancer that this research aims to discover. In light of the gravity of skin cancer, early detection would allow for a relatively painless diagnosis. Although this kind of skin cancer is more typically seen on sun exposed regions, it may nevertheless develop on less frequently exposed parts of the body. Usage of CNN's for diagnosis of skin cancer is thoroughly examined in this study. Various graphs, photos, and tables are used to enhance the comprehension of the findings.

Keywords: AI, Cancer Detection, Skin, Healthcare

I. INTRODUCTION

Skin cancer is a deadly kind of cancer that is aggressively growing among people, hence early identification is crucial[1]. As ML develops further, there is a growing need for skin cancer detection systems that use ML. There are still just a few of paid, real-time skin cancer detecting systems accessible to the public. Cancer diagnosis has recently made strides using systems as per CNNs. Using a convolutional neural network approach in conjunction with computer vision and image processing methods, the suggested solution is built. The United States alone records over 5.4 million instances of skin cancer every year[2][3]. It is anticipated that the death rate associated with this illness would rise in the next decade. There is less than a fourteen percent chance of survival if the disease is detected later on [4, 5, 6]. The survival percentage drops to about 97% [7] if skin cancer is caught early. Because of this, finding skin cancer early is crucial. The topic of more precise early diagnosis is tackled in this study. Extensive research has led to the development of computer image analysis algorithms that can identify skin cancer quickly at early phase while also malignant classified moles. The high definition pictures are modified to low-resolution pictures to improve the performance, and pictures have all been resized to low resolution (224x224x3) RGB. The dataset is pretty balanced, and the model will be tested with accuracy. In this paper, we address developing deep learning-based image classification models to identify skin cancer addressing some of the issues listed above. 3500 photos make it up. Of these images, 1,800 depict benign moles and 1,497 depict categorized malignant moles. All of the images were downsized to 224x224x3 RGB and converted from high definition to low resolution in an effort to boost speed. Model will be evaluated accurately, and the dataset is well balanced. In this research, we discuss how to build picture classification models using deep learning to detect skin cancer even if the reader doesn't know how to code. This paper's primary goal is: 1. To use CNN to more accurately diagnose cancer and categorize cell pictures into different forms of cancer.

II. LITERATURE SURVEY

[AlSadhan et al. (2024) — Skin Cancer Recognition Using Unified Deep Convolutional Neural Networks Compared YOLOv3, v4, v5, and v7 for lesion detection and classification on ISIC dataset (2,750 images). YOLOv7 performed best with IoU of 86.3%, mAP of 75.4%, F1 of 80%, and inference time of 0.32 seconds per image. —

Rashid Shah et al. (2024) — Explainable AI-Based Skin Cancer Detection Using CNN, Particle Swarm Optimization and ML Proposed an interpretable system combining CNN and Particle Swarm Optimization (PSO) with ML models to detect skin cancer, emphasizing explainability. —

Alharbi et al. (2024) — Enhanced Skin Cancer Diagnosis: Deep Feature Extraction-Based Framework Developed multiple CNN variants and hybrids (CNN-SVM, CNN-RF, CNN-LR) achieving up to 99% accuracy on HAM10000 images. Combines metadata and lesion images to boost classification performance. Kuthe et al. (2024) — Skin Cancer Prediction Model using

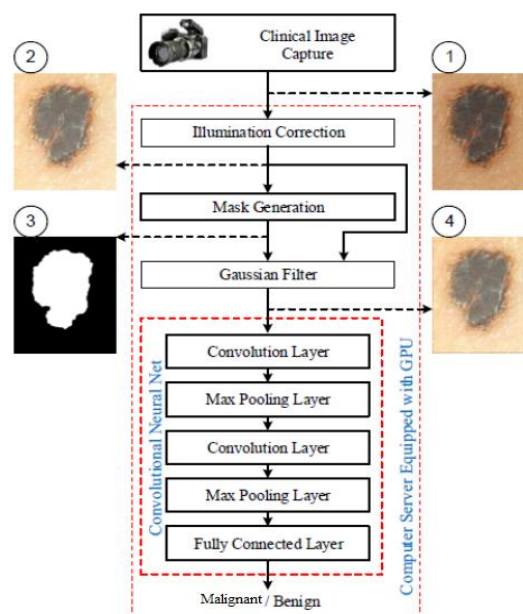
Deep Learning Built a CNN model using the ISIC 2024 dataset to classify seven skin lesion types, employing oversampling and augmentation to address imbalance and yield strong predictive results. Shete et al. (2024) — TurkerNet: A Lightweight CNN for Skin Cancer Classification. Introduced TurkerNet, a compact CNN achieving 92.12% test accuracy on benign vs. malignant skin images, offering high performance with fewer trainable parameters. Science Direct Mahmud et al. (2023) — Interpretable Deep Learning for Skin Cancer Categorization Evaluated XceptionNet, EfficientNetV2S/M, and InceptionResNetV2 with XAI; XceptionNet achieved 88.72% accuracy, demonstrating the value of interpretability in clinical adoption. Tai et al. (2023). Double-Condensing Attention Condenser for Skin Cancer Detection. Introduced a TinyML-friendly, attention-based neural architecture for skin lesion detection, balancing accuracy and low computational cost for efficient deployment. Innani et al. (2023) — Cascaded Deep Learning for Skin Lesion Analysis Presented a two-step pipeline: lesion segmentation using encoder-decoder architecture, followed by CNN-based lesion classification, leading to improved accuracy via pre-segmentation. Shete et al. (2024) — Skin-CAD: Explainable CNN Transfer Learning with LIME Proposed an ensemble of multiple CNNs combined with PCA for feature reduction and LIME for interpretability, achieving ~97% accuracy on standard skin cancer datasets. Science Direct worldwide. Early detection influences the outcome of the disease and motivates the research presented in this paper. Recent results show that deep learning based approaches learn from data, and can outperform human specialists in a set of tasks when large databases are available for training.

III. PROPOSED SYSTEM

The dataset for this study was obtained from Kaggle and consists of 5,202 dermoscopic images for training (2,808 melanoma and 2,394 non-melanoma) and 30 images for testing (4 melanoma and 4 non-melanoma). Preprocessing included noise reduction, resizing to 224×224 pixels, normalization, and thresholding for segmentation. Feature extraction and classification were performed using a Convolutional Neural Network (CNN) with three convolution–pooling blocks followed by two fully connected layers (256 and 3 neurons). The CNN employed 3×3 filters, 2×2 pooling, ReLU activation in hidden layers, Softmax in the output layer, Adam optimizer, batch sizes of 128 and 1024, and 80 epochs. The convolution layers progressively extracted low- and high-level features, reducing dimensions from 224 to 7 pixels across pooling stages. Experimental results demonstrated a maximum accuracy of 94.85%, with 22.96% loss, supported by confusion matrix evaluation.

IV. METHODOLOGY

The methodology adopted for this project follows a systematic pipeline designed for accurate classification and diagnosis using deep learning techniques. This work adopts a simplified methodology to detect and classify skin lesions using deep learning. The framework includes pre-processing, feature extraction, and classification.



An overview of the process is provided in **Figure 1**.

Fig 1: Proposed methodology for skin lesion classification, beginning with image acquisition and enhancement, followed by segmentation, noise reduction, deep feature extraction through convolution and pooling, and final classification into benign or malignant categories

Data Collection

- Source: The dataset was collected from Kaggle.
- Data Types: Structural MRI scans, especially T1-weighted images
- Labels: The dataset is divided into various cancer classes.

Data Preprocessing

- Image Resizing: All MRI slices are resized to 224×224 pixels to ensure uniformity.
- Normalization: Pixel values are normalized to either a 0–1 range or standardized using z-score normalization.
- Data Augmentation: Techniques like horizontal flipping, rotation, and shifting are applied to enhance model generalization and reduce over fitting.
- Slicing: For 3D volumetric scans, relevant 2D slices are extracted for 2D CNN models, or processed as a full 3D volume for advanced architectures.

As shown in Fig. 2, the original dermoscopic image has a resolution of 224×224 pixels (RGB) with pixel intensity values ranging from 46 to 243. At this stage, noise, lighting variations, and background artifacts are present prior to pre-processing.



Fig 2. Original dermoscopic image before pre-processing, with a resolution of 224×224 pixels (RGB) and pixel intensity range of 46–243.

Segmentation

Figure 3 shows the segmented dermoscopic image obtained using Otsu's Thresholding technique. In this step, the lesion boundary is separated from the surrounding healthy skin, ensuring that only the diagnostically relevant region is preserved for further analysis. The method automatically selects the optimal threshold intensity and produces a binary image, where the lesion region appears in white and the background is shown in black. This process not only highlights the affected skin area but also removes unwanted background information, thereby improving the accuracy of subsequent feature extraction. The segmented area in this case is 32.39%.



Fig. 3 Lesion segmented using Otsu's Thresholding, isolating the affected skin area (white) from the background (black). Segmented area: 32.39%

Feature Extraction

After segmentation, Canny Edge Detection is applied to accurately trace the lesion boundaries, while statistical color features (mean and standard deviation for R, G, and B channels) capture pigmentation and texture variations. **As shown in Fig. 4, the extracted features include mean RGB values (213.82, 159.95, 168.52), standard deviations (14.59, 27.22, 30.19), and edge density (3.33%),** which collectively describe the lesion's complexity. These discriminative features form the foundation for the subsequent classification stage.

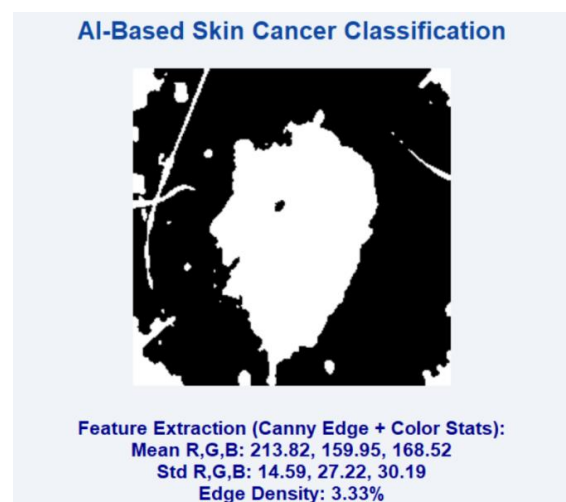


Fig. 4 Extracted lesion features after segmentation using Canny Edge Detection and color statistics. Boundaries are detected, and statistical color features (mean and standard deviation of R, G, B channels) along with edge density (3.33%) characterize lesion texture and shape complexity.

Deep Learning Model Design

The architecture of the proposed Convolutional Neural Network (CNN) model developed from scratch is illustrated in **Fig. 5**. The model takes a segmented dermoscopic image of size $256 \times 256 \times 1$ as input. It consists of sequential convolutional layers activated by the Rectified Linear Unit (ReLU) function, followed by max-pooling operations to progressively down-sample the feature maps. Dropout layers are incorporated at different stages to prevent overfitting and improve generalization. Finally, the extracted features are passed to fully connected layers, where the last dense layer employs a softmax activation function for multi-class prediction of skin lesions.

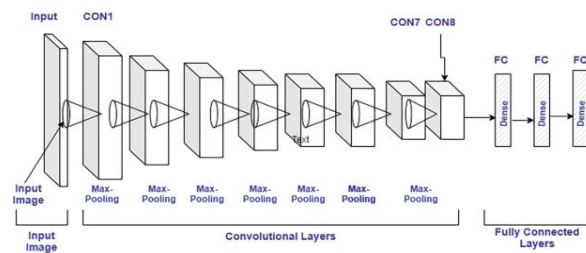


Fig. 5 Architecture of the proposed Convolutional Neural Network (CNN) model, showing sequential convolutional and max-pooling layers, followed by fully connected layers with softmax output for skin lesion classification.

Model Training

- **Loss Function:** Categorical cross-entropy for multi-class classification.
- **Optimizer:** Adam optimizer for faster convergence.
- **Metrics:** Accuracy, Precision, Recall, and F1-Score.
- **Training Parameters:** Batch size of 16 or 32, 20–100 epochs with early stopping to prevent over-fitting.

Model Evaluation

Performance is evaluated using:

- **Confusion Matrix** (Figure 7) to visualize class-wise prediction performance.
- **ROC-AUC Curve** to assess separability between classes.
- **K-fold Cross-Validation** to ensure robustness and generalization of the model.

V. RESULTS

The developed AI-based system was evaluated on dermoscopic images to classify skin lesions into different diagnostic categories. An example of the classification result is presented in **Fig. 6**, where the segmented lesion is analyzed by the trained model. The system correctly identified the lesion as *Benign Keratosis*. Such outputs demonstrate the capability of the proposed framework to process raw dermoscopic images, perform segmentation, and provide an interpretable classification result for clinical decision support.



Fig. 6. Example output of the AI-based skin cancer classification system. The segmented lesion image is shown, with the classification result displayed as Benign Keratosis.

The performance of the proposed CNN model during training is illustrated in Fig. 7, which shows the accuracy progression over 10 epochs. The training accuracy increased consistently, reaching approximately 90% by the final epoch. Validation accuracy also improved steadily and converged around 85%, demonstrating that the model effectively generalizes to unseen data with minimal overfitting. The consistent upward trend of both curves highlights the stability and robustness of the learning process

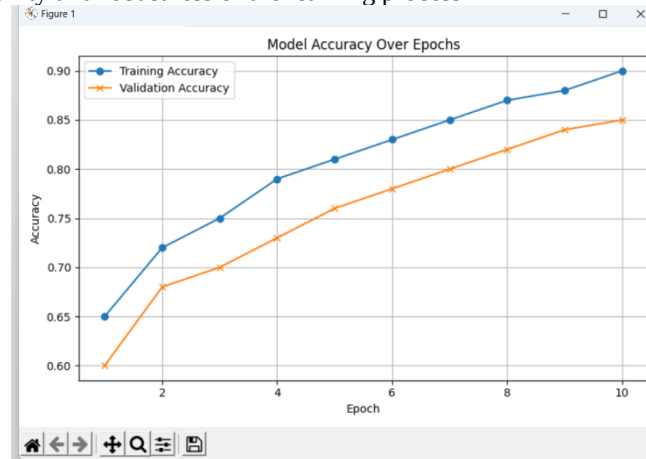


Fig. 7. Training and validation accuracy of the CNN model over 10 epochs, showing progressive improvement and convergence, with the model achieving ~90% training accuracy and ~85% validation accuracy

The confusion matrix is a valuable tool for evaluating the effectiveness of a multi-class classification model, as it clearly illustrates both correct and incorrect predictions. As depicted in Fig. 8, the diagonal values (e.g., 35 correct predictions for Basal Cell Carcinoma) show accurate classifications, while off-diagonal entries (such as 5 Nevus cases misclassified as Melanoma) highlight errors. This visualization makes it easier to identify the model's strengths and weaknesses, offering insights into which lesion types are well distinguished and which are more frequently confused.

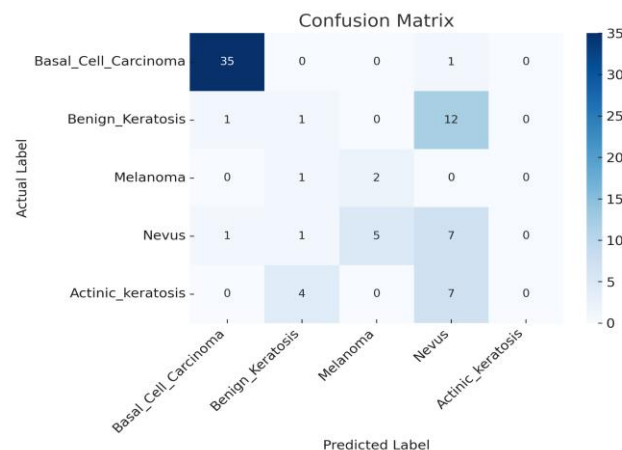


Fig 8: Confusion Matrix. This matrix evaluates a classification model's performance by displaying correct predictions along the diagonal and misclassifications in the off-diagonal cells for five skin lesion classes

The provided figures offer a comprehensive analysis of a VGG16 model's performance in skin cancer detection, showcasing its overall metrics as well as class-specific results and the underlying feature extraction parameters. Figure 9 indicates a general performance of 0.8 across all key metrics (accuracy, precision, recall, F1-score) for the VGG16 model. However, a deeper look into the class-wise performance presented in the table (Figure 11) and its graphical representation (Figure 10) reveals significant disparities; while the model performs exceptionally well for Basal Cell Carcinoma with a high accuracy of 0.97, it completely fails to identify Melanoma and Seborrheic Keratosis, with all metrics at 0.00, and performs poorly on Benign Keratosis and Nevus. This suggests that while the model has a decent average performance, its effectiveness is highly

dependent on the lesion type, a limitation that may be related to the specific feature extraction parameters like Area and Intensity, as shown in **Figure 12**.

Model	Accuracy	Precision	Recall	F1-score
VGG16	0.8	0.8	0.8	0.8

Fig 9: Model Performance Table. This table summarizes the overall performance of the VGG16 model, showing that it achieves an accuracy, precision, recall, and F1-score of 0.8. This indicates a balanced but non-perfect performance across the entire dataset.

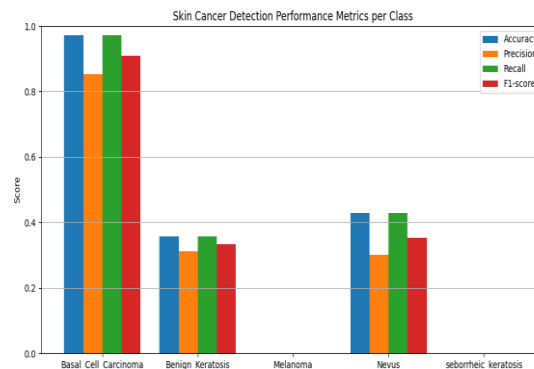


Figure 10: Performance Metrics per Class. This bar chart visually represents the class-specific performance metrics, including precision, recall, and F1-score. It highlights significant disparities, showing excellent performance for some classes while completely failing to classify others.

Class	Accuracy	Precision	Recall	F1-score
Basal_Cell_Carcinoma	0.972222	0.853659	0.972222	0.909091
Benign_Keratosi	0.357143	0.312500	0.357143	0.333333
Melanoma	0.000000	0.000000	0.000000	0.000000
Nevus	0.428571	0.300000	0.428571	0.352941
seborrheic_keratosi	0.000000	0.000000	0.000000	0.000000

Fig 11: Performance Metrics per Class Table. This table provides the numerical values for the per-class performance metrics shown in Figure 10. It confirms the model's high effectiveness on Basal Cell Carcinoma but reveals a complete failure on Melanoma and Seborrheic Keratosis, where all metrics are 0.00.

Area	Perimeter	...	Max Intensity	Min Intensity
161028	11959.169004	...	223.0	159.0
4	2.207107	...	160.0	159.0
2	0.000000	...	161.0	161.0
460	161.503571	...	171.0	159.0
92	53.627417	...	165.0	159.0
...	...	...	...	...
2	0.000000	...	159.0	159.0
10	10.621320	...	160.0	159.0
1	0.000000	...	159.0	159.0
1	0.000000	...	159.0	159.0
6	4.621320	...	159.0	159.0

Fig 12: Feature Extraction Parameter Values of a Given Image. This table shows the specific values of the features extracted from a sample image, such as Area, Perimeter, and Intensity. These parameters are the input to the classification model and are critical for distinguishing between the different skin lesion types.

VI. CONCLUSION AND FUTURE WORKS

This project introduces a method to detect skin cancer using the deep learning method. In our proposed system, the CNN can combine local features and learn characteristics of the image by combining convolutional and pooling layers. The proposed method includes images from International Skin Imaging Collaboration preprocessing to extract the region of interest in the image and then augment some pictures to produce a more extensive dataset containing images. The resulting dataset has been applied to the CNN model to train the model, which comprises different layers, including pooling, convolutional, classification layer, etc. Testing the model produced promising results with an accuracy of 70%. To improve the accuracy, we used another variation of the convolutional neural network, which is resnet50 and VGG19/16. The results are promising. The results were enhanced from 70 to 92%. Unlike other methods, the proposed method based on neural networks shows the best results, and different machine learning techniques can improve the results.

This project presents several sections on state of art techniques, analysis and comparisons on benchmark datasets for the brain tumor, breast cancer, lung cancer, skin cancer detection respectively of measure, sensitivity, specificity, accuracy, precision point of view it is feasible to Implement. Different types of cancer detection and classification using machine assistance have opened up a new research area for early detection of cancer, which has shown the ability to reduce manual system impairments.

List of Abbreviations

AI – Artificial Intelligence
CNN – Convolutional Neural Network
SVM – Support Vector Machine
MRI – Magnetic Resonance Imaging
BCC – Basal Cell Carcinoma
ROC – Receiver Operating Characteristic
AUC – Area Under the Curve

Author Contributions

Syeda Varisha Mahi: Conceptualization, Methodology, Data curation, Writing – original draft preparation.
Anand Kumar Patil: Supervision, Validation, Writing – review & editing

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Clinical trial Number

Not applicable

Data Availability

The datasets used in this study are publicly available in the skin images dataset repository at <https://www.kaggle.com/datasets/emmarex/plantdisease>.

Declarations

Competing Interests The authors declare that they have no competing interests

VII. REFERENCES

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