AI-Based Resource Efficient Image Classifier for Skin Lesions

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Citation | Khan. S, Khan. F, Saddique. U, Khan. S, Jan. A, "AI-Based Resource Efficient Image Classifier for Skin Lesions", IJIST, Vol. 07 Special Issue. pp 316-328, May 2025
Received | April 16, 2025 **Revised |** May 17, 2025 **Accepted |** May 20, 2025 **Published |** May 22, 2025.

Skin cancer and other skin diseases are significant health concerns, and early diagnosis is essential for effective treatment. Traditional diagnostic methods, such as clinical examination and histopathological analysis, are time-consuming, require specialized expertise, and often cause delays in treatment. AI models have the potential to transform this process. While previous research has primarily focused on skin cancer or specific skin diseases, this study takes a broader approach by introducing a novel multiclass classification model. We created a unique dataset combining images from publicly available datasets and new images collected using mobile cameras. The dataset consists of three types of skin cancer and six categories of skin diseases, with both mobile camera and dermoscopic images included. In total, we gathered 6,820 skin lesion images, 4,957 from public datasets, and 1,863 new images to enhance the dataset. Various deep learning models, including VGG16, ResNet50, DenseNet121, MobileNet, and a custom CNN, were tested. While these models performed well with dermoscopy images, they struggled with mobile images. To address this, we implemented a new classification model, YOLOv11, for multiclass classification. This model achieved an impressive 97.5% overall accuracy, with an F1 score of 0.97503, and 99% accuracy for each class, handling both dermoscopy and mobile images effectively.

Keywords: Skin Cancer; Skin Diseases; Deep Learning; Multi-Class classification; AI; Medical Diagnosis; YOLOv11

Introduction:

Skin lesions are one of the most common health problems worldwide, posing significant challenges to healthcare systems [1]. These conditions affect millions of people each year, with skin cancer being one of the most concerning. Skin cancer occurs when skin cells grow uncontrollably, often due to exposure to ultraviolet (UV) radiation from the sun or artificial sources like tanning beds. UV radiation damages DNA in skin cells, leading to mutations that disrupt normal cell function. If not detected early, these mutations can lead to skin cancer [2]. The World Health Organization (WHO) reports that melanoma alone causes over 300,000 new cases annually and results in more than 60,000 deaths each year [3]. According to the Global Cancer Observatory (GCO) [4], melanoma mortality is highest in Europe, with 26,180 deaths, followed by Asia with 13,147 deaths, Latin America and the Caribbean with 5,842 deaths, Africa with 2,859 deaths, and Oceania with the lowest number of deaths at 1,902. Additionally, non-melanoma skin cancers, such as squamous cell carcinoma and basal cell carcinoma, contribute significantly to the cancer burden in other parts of the world.

Beyond skin cancer, other skin diseases like eczema, psoriasis, leishmaniasis, warts, and fungal infections also affect a large portion of the population, causing pain, discomfort, and distress. Delayed or inefficient diagnosis of these conditions can lead to serious complications, making early detection essential. Traditional diagnostic methods, such as clinical inspection, dermoscopy, and histopathology, are effective but time-consuming and require specialized skills [5]. Moreover, limited access to dermatologists often delays diagnosis and treatment. The advancements in AI and deep learning have opened the door to computer-aided systems for detecting and classifying skin conditions, addressing the need for faster, more accessible dermatological services. AI models can accurately classify skin lesions and provide real-time diagnostic support, even in remote areas. Convolutional Neural Networks (CNNs) have shown promising results in classifying skin lesions from dermoscopic images. However, most studies have focused separately on skin cancer or skin diseases, with limited research on unified multiclass classification. Publicly available datasets, like ISIC [6] and HAM10000 [7], primarily contain dermoscopic images, which don't capture the variability in image quality and lighting that real-world images present.

To address these challenges, we created a novel dataset that combines images of both skin cancer and skin diseases. This dataset includes images taken with mobile cameras, as well as dermoscopic images. We gathered data from several publicly available skin disease and skin cancer datasets, supplemented by mobile captured images to increase diversity. To achieve multiclass classification, we trained several state-of-the-art models, such as VGG16, ResNet50, DenseNet121, MobileNet, and a custom CNN. While these models performed well with traditional dermoscopy image datasets, their accuracy dropped significantly when tested with real-world mobile images, highlighting the need for more robust solutions. To enhance accuracy and generalizability, we trained the YOLOv11 [8] model for the multiclass classification of skin diseases and cancers. YOLOv11 outperformed conventional methods, making it a viable solution for real-world dermatological diagnosis.

Literature Review:

Skin cancer is a significant global health issue, with its incidence rates steadily increasing over recent decades. Early and accurate detection is crucial for improving patient prognoses and enabling less invasive treatments [9]. Traditional skin cancer and skin disease diagnoses are heavily dependent on dermatological expertise, which can be time-consuming and subject to variability [10]. However, advancements in artificial intelligence (AI), particularly deep learning and computer vision, have opened new possibilities for accurate skin lesion diagnosis and classification[9], [11]. Several deep learning models have been explored for classifying skin diseases and cancers, particularly using convolutional neural networks

(CNNs) due to their proficiency in image processing [12], [13], [14], [15]. For example, Ahmad Naeem et al. developed a model combining VGG16 and CNNs for the multiclass classification of melanoma, melanocytic nevi, basal cell carcinoma, and benign keratosis, achieving 96.91% accuracy on the ISIC 2019 dataset [14]. This performance surpassed other pre-trained classifiers such as ResNet50, Inception v3, AlexNet, and VGG19. Ehsan Bazgir et al. [16] proposed an automated skin cancer classification system using a deep neural network-based model with an optimized InceptionNet architecture, enhanced by data augmentation and preprocessing techniques. Their model achieved 84.39% accuracy using the Adam optimizer and 85.94% with the Nadam optimizer. Similarly, Sobia Bibi et al. [13] designed MSRNet, a deep model applying contrast enhancement techniques with modified DarkNet-53 and DenseNet-201 models, achieving accuracy rates of 85.4% and 98.80% on ISIC2018 and ISIC2019, respectively. They also suggested using genetic algorithms for hyperparameter selection and marine predator optimization for feature selection.

Neven Saleh et al. [17] tackled skin cancer classification by applying several CNNs, including AlexNet, Inception V3, MobileNet V2, and ResNet 50. They combined machine learning classifiers with optimization methods, such as Grey Wolf Optimization (GWO), resulting in 51 different models. The combination of AlexNet with GWO provided the highest classification accuracy of approximately 94.5% on the ISIC 2017 dataset. However, one limitation of this study was overfitting due to complex model combinations and reliance on a single dataset. In addition to VGG and ResNet, several other pre-trained models have been fine-tuned for skin cancer classification. For instance, Vipin Venugopal et al. [18] used a pre-trained EfficientNetV2-M, surpassing other state-of-the-art models for both binary and multiclass classification, utilizing transfer learning and data augmentation techniques to improve performance on a dataset of 58,032 dermoscopic images. Similarly, Muhammad Zia Ur Rehman et al. adapted MobileNetV2 and DenseNet201 to classify benign and malignant lesions, achieving 95.50% accuracy [19]. Pronab Ghosh et al. introduced SkinNet-16, achieving an accuracy of around 99.19% for benign vs. malignant classification after preprocessing steps like hair and background removal, image enhancement, and feature extraction [20].

The quality and availability of training data are crucial to the performance of AI models in skin cancer classification. Existing publicly available datasets, such as ISBI 2017, ISIC 2018, PH2, and ISIC 2019, have been widely used for comparing AI models [10], [11]. However, these datasets vary in terms of image quality, lesion types, and patient demographics, which can pose challenges for developing robust and generalizable models. The lack of sufficient representation of certain skin types and lesion subtypes in public datasets may introduce biases, limiting the models' applicability in clinical practice. Another challenge is the class imbalance present in skin cancer datasets, where benign lesions outnumber malignant lesions by a significant margin [21]. This imbalance can bias deep learning models toward the majority class, resulting in reduced performance in detecting less common but potentially more dangerous malignant lesions [21]. To address this, Talha Mahboob Alam et al. used data augmentation to balance the dataset and employed AlexNet, InceptionV3, and RegNetY-320 for classification. RegNetY-320 performed best on this balanced dataset. Maryam Tahir et al. used SMOTE Tomek to handle class imbalance in their DSCC-Net model [22], while other studies have used oversampling and cost-sensitive learning approaches [23], leading to improved classification accuracy. The effectiveness of these approaches depends on the dataset and model used.

In this study, we present a systematic approach to address these challenges. Section III outlines our methodology, including the dataset used and the system proposed. Section IV describes the experimental setup, from data preprocessing to network training and performance evaluation. Section V provides a detailed analysis of the results, discussing the

performance and implications of our proposed system. Finally, Section VI concludes the paper, summarizing the key findings, contributions, and future directions.

Objective:

The primary objective of this research was to develop a multiclass classification model for skin cancer and skin diseases that can accurately classify skin lesions in both dermoscopic and mobile-captured images and to address the challenge of limited availability of mobile-captured images, we also developed a novel dataset containing both dermoscopic and mobile-captured images.

Methodology:

Employed Dataset:

To develop an effective multi-class classification model for skin cancer and skin diseases, we first assembled a diverse dataset by merging publicly available sources with newly acquired images. The dataset consists of nine classes: three skin cancer classes (melanoma, basal cell carcinoma, and squamous cell carcinoma) and six skin disease classes (eczema, psoriasis, leishmaniasis, acne, tinea, and warts molluscum).

Our dataset was compiled from several public datasets, including ISIC [6], HAM10000 [7], med images Computer Vision Project [24], skin cancer Computer Vision Project [25], Skin diseases Segmentation Computer Vision Project [26], skin Computer Vision Project [27], and the New Mod Computer Vision Project [28], in addition to images sourced from mobile phone cameras. Initially, we collected 3,957 skin disease images and 1,000 skin cancer images from these public databases. To enhance the diversity of the dataset and improve model generalization, we supplemented the collection with an additional 1,000 skin disease images and 863 skin cancer images. This expanded dataset is one of the largest multi-class collections of skin condition images available, ensuring robust representation of a wide variety of skin disorders.

Random samples from the skin cancer and skin disease classes are shown in Figure 1 and 2, which illustrate the dataset's diversity and heterogeneity. A summary of the class-wise distribution of images is provided in Table 1. This comprehensive dataset is designed for training deep learning models, especially those focused on classification, offering a more accurate and realistic representation of skin disorders as they would appear in real-world clinical settings.

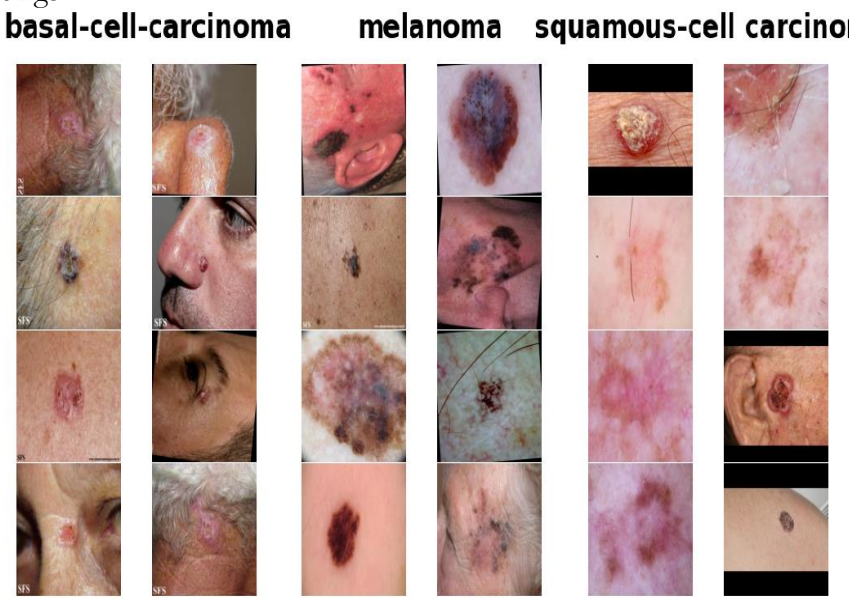

Figure 1. Random Sample Images of Skin Cancer

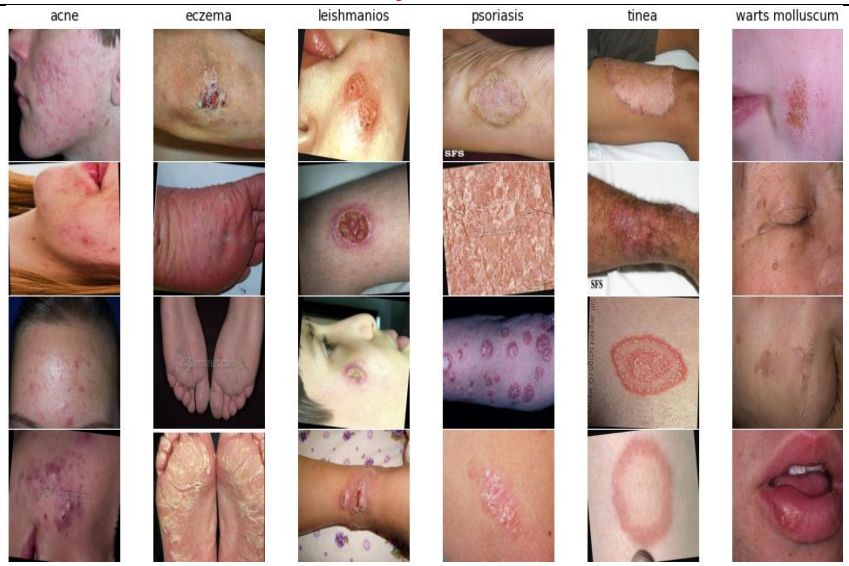

Figure 2. Random Sample Images of Skin Diseases

Table 1. Distribution of Publicly Available and Self Captured Images across Classes

Class	Images Distribution Per Class		
	Total Images	**Publicly Available**	**Self-Captured**
BCC	553	300	253
Melanoma	844	594	250
SCC	439	293	146
Acne	688	554	134
Eczema	1219	1070	149
Leishmaniosis	216	171	45
Tinea	591	470	121
Warts Molluscum	763	608	155
Psoriasis	1480	1084	396
Total	**6820**	**4957**	**1863**

YOLO-v11

The YOLOv11 [8] model represents a significant advancement in the YOLO series, particularly for classification tasks, building upon the developments of earlier versions such as YOLOv8, YOLOv9, and YOLOv10. While YOLOv11 is traditionally associated with object detection, it also performs exceptionally well in classification tasks due to its efficient feature extraction and processing capabilities. Key components such as the C3K2 and C2PSA blocks, as illustrated in Figure 3, enhance the processing of spatial information. The C3K2 block uses small 3x3 kernels to maximize computational efficiency while improving feature representation. Meanwhile, the C2PSA block utilizes attention mechanisms to focus on salient areas within an image, which is crucial for detecting fine-grained details.

Unlike the detection model, YOLOv11-cls (the classification-specific version) omits the neck (e.g., the SPFF module), as multi-scale feature aggregation is unnecessary for classification. Instead, the backbone directly extracts high-level features, which are passed to the classification head. This results in an efficient and lightweight design. The classification head then projects these extracted features into class probabilities, enabling the model to make accurate predictions with a fast and resource-efficient architecture. As a result, YOLOv11 is a state-of-the-art image classification model, that combines strong performance with an efficient design.

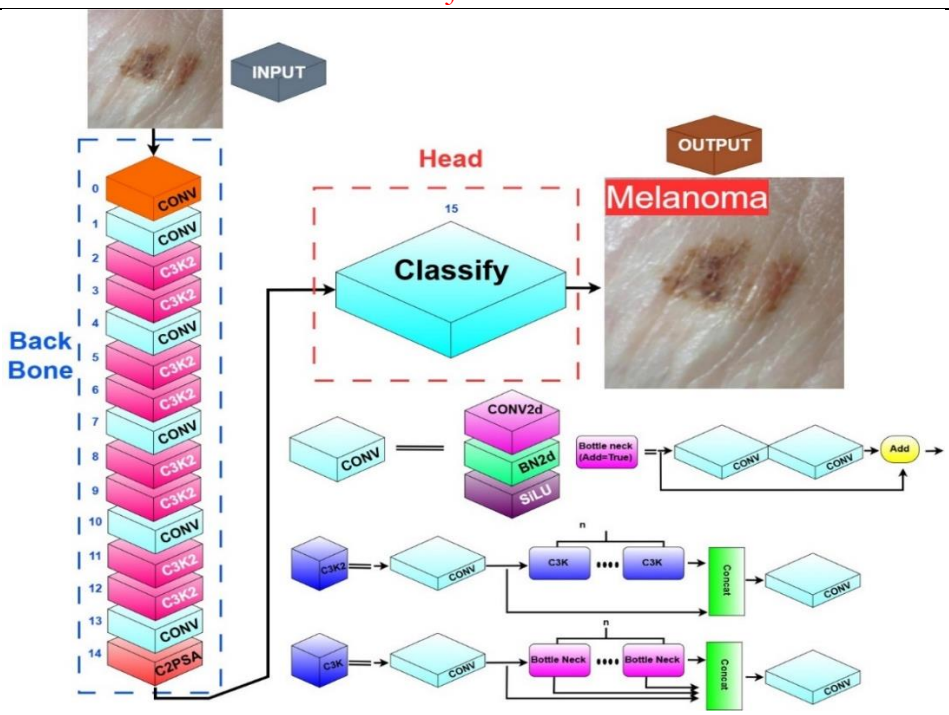

Figure 3. Yolo-v11 Object Classification Architecture

Proposed Framework:

The proposed study adopts a uniform approach for multi-class classification of skin cancer and skin diseases using the YOLOv11 model. The pipeline as shown in Figure 4 begins with data collection, followed by preprocessing, hyperparameter tuning, and evaluation using standard metrics. The best-performing model is then selected for multiclass classification. The process begins by capturing a skin lesion image using a smartphone, which is then fed into the model for preprocessing. This preprocessing step includes resizing, normalization, and data augmentation to enhance the model's robustness. Once the image is preprocessed, it is passed through the YOLOv11 classification model, which extracts important features related to the skin condition from the image. If the model's confidence in the detected area is below a threshold of 0.5, the image undergoes additional preprocessing and is re-evaluated. If the confidence value meets or exceeds the 0.5 threshold, the extracted features are mapped to classify the image into one of the nine classes, which include three skin cancer types and six skin conditions.

The final output of the system is the class label of the lesion, enabling accurate diagnosis. The system ensures iterative refinement by reprocessing uncertain cases until confident classification is achieved, thus improving diagnostic accuracy and real-world applicability. The operational workflow of the system is illustrated in Figure 5.

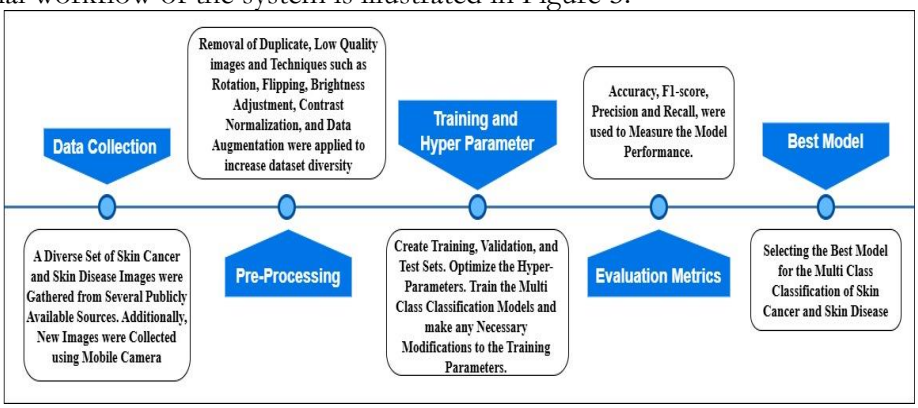

Figure 4. Flow Diagram of Detailed Methodology

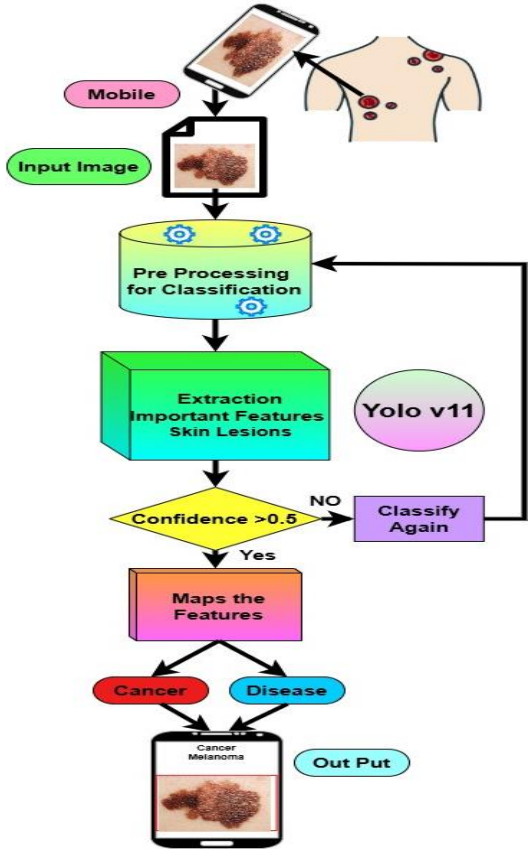

Figure 5. Block Diagram of Proposed Workflow

Experimental Setup:

Data Pre-processing:

The dataset was split into training, validation, and test sets in a 70:15:15 ratio. Extensive preprocessing was performed on the dataset before training to ensure high-quality input for the model. This preprocessing included the removal of duplicate, low-quality, and noisy images to enhance model performance. Techniques such as rotation, flipping, brightness adjustment, contrast normalization, and data augmentation were applied to increase dataset diversity and improve the model's resilience. Data labeling was carried out manually through renaming. Additionally, the images were resized and normalized to meet the input requirements of the YOLOv11 classification model.

Networks training:

The system proposed in this research was developed and tested on a computer with an Intel Core i7-10700 processor running Windows 10 at 2.90 GHz, paired with an NVIDIA GeForce RTX 3060 GPU with 12 GB of VRAM, and 16 GB of system RAM. The implementation was carried out using Python 3.12, with the PyTorch framework serving as the primary deep-learning library. A summary of the training parameters for classification is provided in Table 2.

Table 2. Training Parameters

No.	Parameters for Classification Model	
	Hyperparameters	**Details**
1	Picture size	640 x 640
2	Epochs	100
3	Batch size	16
4	Workers	8
5	Patience	40

Analysis of Computational Efficiency:

A YOLO-based image classification pipeline was implemented and evaluated in two phases: inference and training. During inference, a custom script processed a structured test dataset, where each subdirectory represented a distinct class, to compute top classification predictions. The pipeline achieved an average processing time of approximately 12 ms per image, with 8.7 ms for preprocessing, 3.3 ms for inference, and negligible postprocessing time, as shown in Table 3.

Table 3. Per-Image Computational Performance

Metric	Computational Efficiency at 640×640 Resolution			
	Preprocess (ms)	Inference (ms)	Postprocess (ms)	Total (ms)
Minimum	6.4	2.5	0.0	8.9
Maximum	17.5	10.4	0.1	28.0
Average	8.7	3.3	≈ 0.01	12.0

Evaluation Metrics:

To comprehensively evaluate the effectiveness of the proposed classification model, a range of assessment criteria were employed, including Accuracy, F1-Score, Precision, Recall, and the Confusion Matrix. These metrics provide a thorough performance analysis of the model's ability to accurately classify diverse categories. Accuracy measures the overall classification correctness, while Precision and Recall assess the model's ability to classify positive cases and minimize false positives and false negatives, respectively. The F1-Score computes the weighted average of Precision and Recall, offering a balanced evaluation metric for imbalanced classes. The Confusion Matrix provides a detailed breakdown of true positives, true negatives, false positives, and false negatives, offering insights into the model's classification bias. The selection of these measures ensures a comprehensive assessment of the model's performance, addressing class imbalance and misclassification issues. The final performance analysis was conducted on diverse datasets to evaluate the model's generalizability and robustness.

Accuracy:

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

Where:

- TP: Stands for True Positive.
- TN: Stands for True Negative.
- FP: Stands for False Positive.
- FN: Stands for False Negative.

F1-Score:

$$F1 = 2 * \frac{P*R}{P+R} \quad \text{Eq (2)}$$

Where:

- P: Stands for Precision.
- R: Stands for Recall.

Precision:

$$P = \frac{TP}{TP+FP} \quad \text{Eq (3)}$$

Recall:

$$R = \frac{TP}{TP+FN} \quad \text{Eq (4)}$$

Results:

Using the proposed dataset, the performance of different classification models exhibited significant variations, as shown in Table 4. Among all the models, YOLOv11 achieved the highest accuracy of 97.5%, with precision, recall, and F1-Score all reaching 0.97, making it the best model for skin disease and cancer classification. The accuracy for each class

was consistently around 99%, demonstrating the model's reliability across various skin conditions. The confusion matrix, shown in Figure 6, illustrates the classification performance and misclassification patterns. In contrast, the VGG16 and custom CNN models performed poorly, with accuracies of 79.5% and 23%, respectively, indicating their limited generalization ability on this diverse dataset. These results emphasize the advantage of utilizing advanced architectures like YOLOv11 for real-world dermatological classification. The training and validation loss curves, shown in Figure 7, indicate the model's stability during training. Additionally, Figure 8 presents the test results on unseen images, highlighting YOLOv11's efficiency in accurately classifying various skin conditions.

Table 4. Test Results of the Classification Models

Model	Performance Evaluation Metrics for Classification			
	Accuracy	F1 Score	Precision	Recall
YOLO v11	**97.5%**	**0.9750**	**0.9753**	**0.9751**
YOLO v8	94.6%	0.9455	0.9472	0.9461
DenseNet 121	81.2%	0.8114	0.8180	0.8126
MobileNet	82%	0.8208	0.8243	0.8209
ResNet 50	87.4%	0.8745	0.8774	0.8747
VGG 16	79.5%	0.7950	0.8102	0.7950
Custom CNN	23%	0.0949	0.1508	0.2308

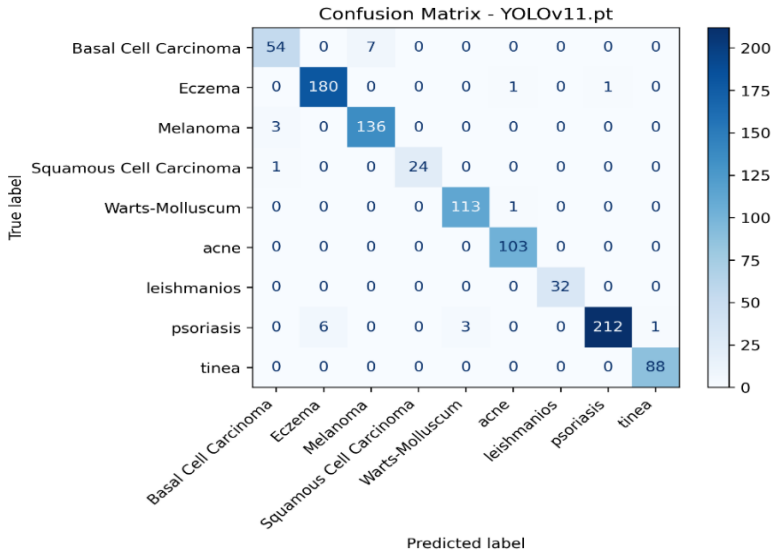

Figure 6. Confusion Matrix

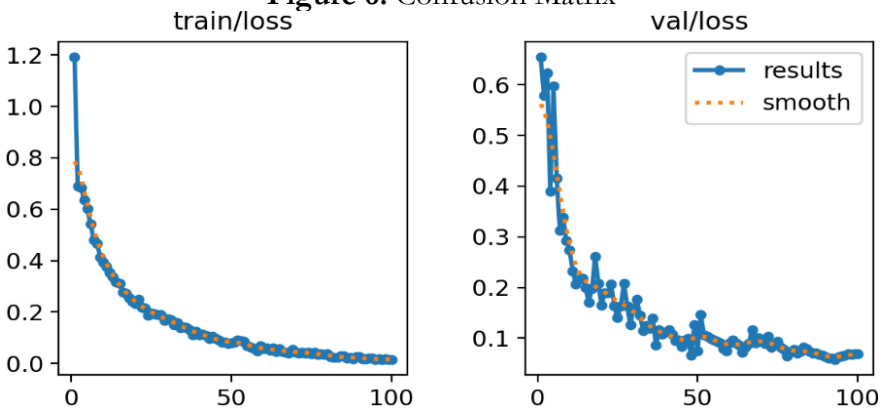

Figure 7. Training and Validation Loss Curve

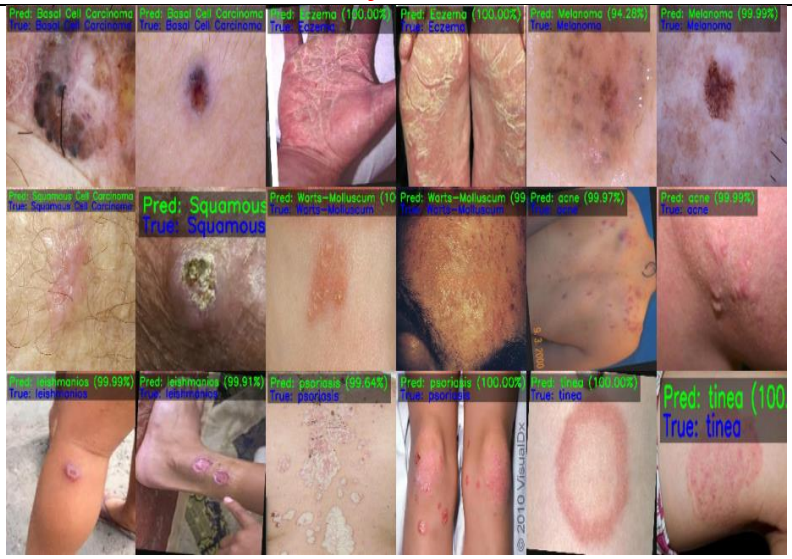

Figure 8. Performance of the Proposed System on Unseen Images

Discussion:

The experimental results demonstrate the superior performance of the proposed YOLOv11-based framework for the multi-class classification of skin cancer and skin diseases. As highlighted in Table 5, the proposed model achieved an accuracy of **97.5%**, outperforming several state-of-the-art models applied on benchmark dermoscopic datasets. For instance, Ahmad Naeem et al. [14] employed VGG16 with CNNs on the ISIC 2019 dataset and achieved an accuracy of 96.91%, whereas Neven Saleh et al. [17] used AlexNet optimized with the Grey Wolf Optimizer (GWO) and reported 94.5% accuracy. Similarly, Vipin Venugopal et al. [18] used EfficientNetV2-M on the ISIC 2019 and HAM10000 datasets and reported accuracies of 95.49% and 94.80% respectively across different classes. Although these models performed well on dermoscopic images, they did not incorporate real-world mobile-captured images, which limits their practical applicability in diverse clinical environments.

In contrast, our study uniquely combines dermoscopic and mobile-captured images, addressing real-world scenarios where high-end dermoscopic equipment may not be available. This enhances the model's adaptability in low-resource or remote settings, which is a significant advancement over prior work. Notably, our model also supports multi-class classification (covering both three types of skin cancer and six common skin diseases), whereas most prior works focused solely on binary or limited multi-class cancer classification.

Additionally, earlier models like those proposed by Ehsan Bazgir et al. [16] using InceptionNet (85.94% accuracy) and Zia Ur Rehman et al. [19] using MobileNetV2 with DenseNet201 (95.50% accuracy) did not consider mobile image sources or extensive disease variety. These comparisons underscore the novelty and strength of our model in terms of both accuracy and versatility.

Table 5. Comparative Analysis of Proposed Work with Existing Studies

Research work	Dataset	Model	Results	Dermoscopic Image Classification	Mobile Image Classification	Multi-Class (Cancer + Diseases)
This Study	**(6820 Images) Dermoscopic + Mobile Captured Images**	**Yolo v11**	**97.5%**	**Yes**	**Yes**	**Yes**
Ahmad Naeem et al.	ISIC 2019 Dermoscopic	VGG16 with CNNs	96.91%	Yes	Nil	Nil

[14]	Images					
Ehsan Bazgir et al. [16]	Custom Dataset Dermoscopic Images	InceptionNet	85.94%	Yes	Nil	Nil
Neven Saleh et al. [17]	ISIC 2017 Dermoscopic Images	AlexNet with GWO	94.5%	Yes	Nil	Nil
Vipin Venugopal et al. [18]	ISIC 2019 HAM10000 Dermoscopic Images	EfficientNetV2-M	95.49 94.80	Yes	Nil	Yes
Zia Ur Rehman et al. [29]	ISIC Archive Dermoscopic Images	MobileNetV2 and DenseNet201	95.50%	Yes	Nil	Nil

Conclusion:

The prime aim of the research was to address the challenges of multi-class classification of skin cancer and skin diseases using deep learning models. We successfully bridged the gap between research datasets and real-world medical diagnostics by collecting a diverse dataset of 6,820 images, including images from mobile cameras and dermoscopic devices. After evaluating several state-of-the-art classification models, YOLOv11 demonstrated the best performance, achieving 97.5% accuracy and an F1-score of 0.9750. Our approach enhances real-world generalization of data, making it a valuable tool for assisting dermatologists and physicians.

Future work can expand the dataset to include more skin disease and cancer classes, further improving the model's generalization. Additionally, incorporating cancer staging classification could provide additional diagnostic information, facilitating earlier detection and better treatment planning. Further improvements can also be achieved by integrating explainable AI methods, such as Grad-CAM or LIME, to enhance model interpretability and foster better predictions in clinical settings.

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