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Development of a Convolutional Neural Network-Based Web Application for Automated Skin Disease Classification

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ABSTRACT

Dermatological disorders remain a significant global healthcare challenge, affecting millions of individuals and contributing to increased disease burden, particularly when delayed or inaccurate diagnosis affects treatment outcomes. Although artificial intelligence has demonstrated substantial potential in supporting dermatological diagnosis, many existing approaches are constrained by limited dataset diversity and insufficient deployment into practical healthcare environments. This study aimed to develop a Convolutional Neural Network (CNN) based web application for automated skin disease classification using dermoscopic images. A deep learning framework was implemented to automatically extract discriminative visual features from annotated dermoscopic skin lesion datasets. Image preprocessing techniques, including resizing, normalization, and data augmentation, were applied to enhance model generalization and reduce overfitting. The developed CNN model was evaluated using standard classification metrics, including accuracy, precision, recall, and F1-score, and subsequently integrated into a web-based application to enable real-time disease prediction. Experimental evaluation demonstrated that the system effectively classified multiple skin disease categories and provided automated predictions through an accessible web interface. The deployment of the trained model improved practical usability by providing a rapid and intelligent decision-support tool for preliminary dermatological assessment. The study highlights the potential of CNN based image classification and web-enabled artificial intelligence systems in supporting early skin disease detection, improving diagnostic accessibility, and enhancing clinical decision-support capabilities, particularly in healthcare settings with limited access to dermatology specialists.

KEYWORDS: Artificial Intelligence (AI); Convolutional Neural Network (CNN); Deep Learning (DL); Skin Disease Classification; Dermoscopic Images; Web-Based Diagnostic System.

I. INTRODUCTION

Skin diseases are one of the biggest problems for people worldwide, with various health impacts, including medical, mental, and economic ones. With an increase in diseases such as eczema, infection, and cancer, there is a greater need for prompt and correct diagnosis. Among all cancers that affect the skin surface, there is a very serious type called “malignant melanoma” which has a poor prognosis if not detected at an earlier stage and treated quickly enough for better outcomes. Current estimates suggest that there are approximately 2-3 million new cases of non-melanoma skin cancer and approximately 132,000 melanoma cases diagnosed each year globally, highlighting the necessity of efficient diagnostic tools for early detection. (Noo et al., 2025). Though there have been significant developments within dermatology as a field of medicine;

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traditional methods for diagnosing diseases affecting skin still depend heavily upon physical inspection (dermoscopy) along with microscopic analysis performed professionally at specialized centers under expert doctors' guidance. Although such tests are essential for diagnosis, there is a high degree of subjectiveness among doctors as well as differences between them (inter-observer). These challenges are especially apparent in developing countries and resource-limited healthcare systems, where dermatologist shortages often lead to delayed diagnoses and incorrect treatment choices (Khan et al., 2025; Lee et al., 2024). Thus, there is a growing need to develop more effective intelligent computer aided diagnostics systems that would enhance diagnostic reliability and assist doctors with their everyday medical decisions. The rapid development of AI and ML has opened new prospects for improving medical imaging analysis and disease diagnosis. Specifically, DL methods enable automatic feature extraction for images without manual intervention through their ability to automatically analyze and process images. Among them, CNNs are among the best methods for dermatological image analysis because they can learn hierarchical representations of lesion features without manual feature engineering. Previous studies have shown that CNN-based models can achieve high classification performance for several dermatological conditions, indicating their potential to improve diagnostic efficiency, reduce human error, and enable early clinical interventions. (Khan et al., 2025; Patel et al., 2024). Despite this progress, some issues remain unresolved. Several pre-existing AI-based skin disease classification models were created with limited to unbalanced datasets, which limits their reliability and applicability to various patient populations and skin types (Guo et al., 2022). In addition, there is a lot more work done regarding creating classifiers rather than applying them for medical use. Therefore, relatively few studies have incorporated deep learning models into available online applications that provide real-time diagnosis assistance for practical healthcare settings (Khan et al., 2025). There is a gap in the design of algorithms for use, which hinders the effective integration of artificial intelligence techniques within healthcare services, such as skin treatments.To address this problem, a device with good discriminating power should be developed, which is also convenient for use by people who are unable to access it directly. Thus, this study created a CNN-based website to automatically classify skin diseases using dermatoscope images. Systematic images are pre-processed; automatic deep features are extracted by a model that is then evaluated with predefined measures of efficacy and deployed on-demand through a web interface for immediate diagnosis assistance availability. The model design and implementation were integrated in this study, which goes beyond the efficacy of mere algorithms in demonstrating the viability of developing smart diagnostic tools within everyday medical care environments. This research contributes to the growth of artificial intelligence (AI)-based healthcare through an adaptable model for the quick, dependable, and automatic diagnosis of skin diseases. Deep learning integrated online for diagnosis can increase the accessibility of dermatology care, provide better clinical decision support (CDS), and allow for faster diagnosis, especially when specialists are scarce. This shows that the effective application of artificial intelligence will improve healthcare services and develop smarter tools for better skin disease diagnosis.

II. RELATED WORKS

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Artificial intelligence (AI) has greatly influenced dermatological diagnosis through the precise analysis of skin lesion images to provide appropriate healthcare solutions. Improvements to ml and dl are making automatic diagnostics for skin diseases much more precise. Among these approaches, deep learning has gained considerable attention because of its ability to automatically learn discriminative image features without relying on manually engineered descriptors. CNNs are currently the most effective deep learning model for skin disease classification because of their better ability to capture multi-scale information from images of diseases. In contrast to traditional ml techniques, which require manual data preprocessing for feature definition, CNN's can self-learn by identifying key dermatoscopic or clinical image elements, such as asymmetrical lesions ANAs borders, and colors. This capability has significantly improved the diagnostic accuracy of various dermatological disorders. Numerous studies have shown that CNN-based algorithms are effective for automatic diagnosis of skin diseases. Khan et al. (2025) reported that deep learning models achieved diagnostic accuracies exceeding 90% for common dermatological conditions, including acne, eczema, and psoriasis, highlighting the potential of AI-assisted diagnosis to complement clinical expertise. Similarly, Patel et al. (2024) observed that AI-supported diagnostic systems improve diagnostic consistency while reducing dependence on specialist interpretation, particularly in healthcare environments with limited dermatological expertise. The results indicate an improvement in medical productivity through artificial intelligence-based diagnostics, decreased inconsistency among diagnoses, and quicker identification of diseases. Increasingly, public access to dermatoscopy images is available in online databases, which have also contributed significantly to the development and implementation of automatic detection systems for skin diseases. Quality datasets for images were used by scientists who developed more complex DL algorithms that could accurately differentiate healthy from diseased tissue at a very good rate. In addition, transfer learning with pre-trained models, such as ResNet, VGG, and EfficientNet, has increased classification accuracy and decreased computation and learning times. These changes increase the versatility of DL applications for medical imaging data and promote their use in healthcare studies.

However, despite such great progress, there are still some constraints on their implementation. One of the limitations found in earlier studies was the limited sample sizes or imbalanced classes that could affect performance or transferability to other groups. Dataset imbalances can exacerbate predictive biases, as they tend to favor diseases with more samples and lower specificity of classifications for minority groups. Thus, such model designs might be effective for testing purposes but less reliable when used clinically. Another constraint is the translation lag from research to practical application. Although several studies have shown good accuracies of classification with CNN networks, most are still lab-based and do not offer any way for implementation by healthcare workers while performing their jobs daily. The lack of user-friendly diagnostic tools reduces accessibility and decreases the potential healthcare impact of accurate classification models. Therefore, the implementation and application of AI by doctors for diagnosing diseases through artificial intelligence are still at an advanced stage, although there have been significant improvements in the methodologies used. From what is known so far, there are some limitations of current approaches, such as CNN-based DL for automatic diagnosis, but there is still room for improvement in terms of its robustness, availability, and practicality. Solving them requires more than good classifiers for the dataset; this technology should also be integrated into a system that is usable as part of the healthcare services delivery process. Thus, our study proposes a CNN-based website to automatically classify skin diseases by performing preprocessing on images and then feeding them through DL models with metric analysis, as well

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as testing its effectiveness on live websites. This study bridges this gap by combining the creation of algorithms with their application, thereby bridging the divide between laboratory-developed AI applications and the clinical use of such devices for diagnostic purposes.

III. METHODOLOGY

The research used deep learning techniques for developing, deploying, and operating a self-healing skin disease diagnostic tool with CNN's. It included 5 steps data gathering, image processing algorithms creation testing of these models on websites for implementation purposes. Overall process is geared for automatic features extraction, diagnosis accuracy as well easy deployment of this system via a web-based app.

A. Research Design

This is a controlled experiment with supervision of dl (deep-learning). The CNN model has been learnt from a set of data containing dermatoscopic pictures for distinguishing between various types of skin disorders by extracting their distinctive appearances visually. The supervised approach is chosen as there were pre-defined classes of diseases available for classification within our data set which allowed us develop a relationship among images with their diagnoses. The architecture was suitable to evaluate how well a CNN can be used as part of automatic skin lesion recognition system.

B. Data Set Collection and Preparation

A variety of dermatoscopic pictures from various diseases are used as training data for this algorithm creation process. Before modelling was done, every picture has been preprocessed for better accuracy of results as well as flexibility while applying it on other datasets. The process included picture resampling for an equal-size of input space suitable to use as input by CNN models; normalizing pixels so that they are on similar scales (intensity). The augmentation tasks involved stochastic transformations of images which helped our neural network acquire a more resilient representation for each given capture setting up, respectively. Then, this data set is divided up for use as a test set of models while also being used by them when they are trained on it.

C. CNN Model Development

Convolutional neural network is used for multi-class skin diseases classification task. CNNs learned a hierarchy of images via convolutions then pools, then classified diseases with fc nets. While learning, this algorithm was continually adjusting of weights to minimize errors from classifying data with help of propagation rule for gradients. Learning allowed a network of diseases for distinguishing between similar but distinct lesions by their morphological features like coloration patterns; surface textures as well as structures within them. CNN's did not require hand-crafted features so they could be fed as images directly to a classifier which improved its accuracy significantly.

D. Model Performance Evaluation

Accuracy, precision, recall, and f1 score were used to assess the model's prediction accuracy. The indicators offered supplementary indices for total predictivity accuracy rates as well as specificity

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ratios along with a consideration on sensitivity-to-precision ratio. Also, we used for classifying diseases' accuracy with help from cm's analysis; there are some cases where it is possible that an error occurred while predicting correctly. These assessments collectively gave an overall picture on how well this categorization model was effective as well reliable enough for use.

E. Web-Based System Deployment

For better usability of this project, we have incorporated our trained CNN algorithm on an online platform which enables live diagnosis from patients' images. Deployment platform allows for uploading dermatoscopic pictures via a user-friendly interface; then our pre-trained algorithm analyzes this picture instantly to predict what type of skin condition it is likely being diagnosed with. The implementation approach extends our tested framework to a practical health care application that can be used for quick skin diagnosis within standard medical settings.

IV. RESULTS AND DISCUSSION

A. Experimental Setup and Model Configuration

The proposed system for classifying skin diseases using CNN is developed with a deep learning model aimed at automatic image recognition and online deployment. The experimental setup comprised Python programming tools, PyTorch deep learning libraries, the ResNet50 architecture, and Streamlit for deployment purposes. The HAM10000 dermoscopy dataset served as the test set for training.

Table 1: Experimental Setup and System Configuration

Component	Specification	Details
Programming Language	Python 3.12	PyTorch, torchvision, scikit-learn
Deep Learning Framework	PyTorch 2.x	Custom ResNet50 pipeline
Model Architecture	ResNet50	50-layer residual network with modified classification head
Dataset	HAM10000	10,015 dermoscopic images; 7 disease classes
Input Image Size	224 × 224 pixels	RGB image resizing
Dataset Split	70:30	7,011 training and 3,004 testing images
Optimizer	Adam	Learning rate = 0.001
Loss Function	CrossEntropyLoss	Multi-class classification
Training Epochs	5	Batch size = 16
Deployment Platform	Streamlit	Web-based image upload and prediction

ResNet50 model is chosen as residual learning networks (rln) can extract deep image representations and minimize noise issues of dnn. Classification model has been updated for predicting seven diseases of skin and blood vessels whereas streamlit made it possible to deploy this solution easily on a website.

B. Dataset Distribution and Preprocessing

The study used the HAM10000 dataset, which contains 10,015 dermoscopy images from the International Skin Imaging Collaboration (ISIC) database. There were 7 diagnosed conditions that corresponded to various kinds of skin diseases included as part of this data set.

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Table 2: Dataset Class Distribution and Train/Test Partition

Class ID	Disease Class	Total Samples	Training (70%)	Testing (30%)
0	Melanoma	1,113	779	334
1	Nevus	6,705	4,694	2,011
2	Basal Cell Carcinoma	514	360	154
3	Benign Keratosis	1,099	769	330
4	Dermatofibroma	115	81	34
5	Vascular Lesion	142	99	43
6	Actinic Keratosis	327	229	98
Total		**10,015**	**7,011**	**3,004**

There is a high degree of imbalanced data where nevus has more instances compared to dermatofibromas & vascular lesions which have lesser number each. This is an existing problem with medical imaging classification as models can be skewed towards majority classes. To improve model generalization, preprocessing techniques including resizing, tensor conversion, random rotation, and horizontal flipping were applied before training.

C. Model Training Performance

CNN model is trained by Adam optimizer and learning rate is 0.001. Training was done for 5 epochs with a batch size of 16 and CrossEntropyLoss as the optimization objective.

Table 3: Training Loss Progression Across Epochs

Epoch	Training Loss	Observation
1	446.9541	Initial high loss during early learning stage
2	409.3907	Rapid reduction as feature extraction improved
3	383.7904	Continued improvement in pattern recognition
4	372.6853	Model stabilization and convergence improvement
5	392.0572	Slight increase due to remaining imbalance effects

Training loss went from 446.95 to 372.69 over 4 epochs, showing that we are learning to recogni ze dermatoscopic features. A small improvement is seen at epoch 5 which may be due to a proble m of optimality variability (class imbalances) as well short learning time.

D. Overall Classification Performance

The trained model was evaluated using accuracy, precision, recall, and F1-score.

Table 4: Overall Model Performance on Test Dataset

Metric	Value	Interpretation
Accuracy	68.22%	Overall, correctly classified samples

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Precision	56.25%	Reliability of positive predictions
Recall	68.22%	Ability to identify actual disease cases
F1-score	61.47%	Balance between precision and recall

The model achieved an overall accuracy of 68.22%. This shows how well a cnn network can rec ognize features from images but it is important for us know if there were imbalances within datas ets affecting results as well. Major nevus types performed well and were easily categorized wher eas minor ones are harder for classification purposes.

E. Per-Class Classification Performance

For an analysis on how well this predictor performs for each category separately we did a classification with precision, recall, f1 score & support. While precision gives an average rating for models' effectiveness; specificity measures specifically what each category does better than others among diseases diagnosed by them.

Table 5: Per-Class Classification Performance of the CNN Model

Class ID	Disease Class	Precision	Recall	F1-Score	Support
0	Melanoma	0.45	0.39	0.42	353
1	Nevus	0.76	0.93	0.84	1,968
2	Basal Cell Carcinoma	0.00	0.00	0.00	34
3	Benign Keratosis	0.00	0.00	0.00	345
4	Dermatofibroma	0.00	0.00	0.00	47
5	Vascular Lesion	0.27	0.44	0.34	162
6	Actinic Keratosis	0.00	0.00	0.00	96
	Overall Accuracy			**0.68**	**3,005**
	Macro Average	0.21	0.25	0.23	3,005
	Weighted Average	0.56	0.68	0.61	3,005

There are significant disparities between predictions for these diseases that have been categorized as follows: Seven Nevus class achieved best results with precision score of 0.76, recall score of 0.93, and F1-score of 0.84. The high score can be attributed to a greater presence of it on the HAM10000 dataset which allows for better feature extraction by the model from that group. On contrary to this group of minorities such as basal cell carcinoma (bcc), benign keratoacanthoma, dermatofibromas & actinics are not well classified. The outcome is due to a class imbalanced problem and deep learning algorithms can have predictive biases for more representative groups. Similar challenges have also been identified in medical image classification studies where imbalanced classes affect model generalization and decrease sensitivity of minority classes.

Melanoma had medium predictive value, with a sensitivity of 0.45 and specificity of 0.39. The system did detect a few cases of melanoma but it is necessary to improve this as there are false negatives for cancer types that have important medical significance. The vascular lesion category achieved an F1-score of 0.34, indicating partial learning of class-specific visual features.

F. Confusion Matrix Analysis

To analyze this data more closely, we have looked at a measure called 'the confusion matrix'.

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Table 6: Confusion Matrix-Based Observations by Disease Category

Disease Class	Correctly Predicted	Major Observation
Melanoma	138	39% sensitivity; frequently confused with Nevus and Vascular Lesion
Nevus	1,840	Strongest performance with approximately 93% recall
Basal Cell Carcinoma	0	Completely undetected due to limited representation
Benign Keratosis	0	Misclassified mainly as Nevus or Melanoma
Dermatofibroma	0	Prediction affected by minority class representation
Vascular Lesion	72	Partially distinguished from other categories
Actinic Keratosis	0	Frequently confused with other lesion groups

Confusion matrix shows how data set imbalances affect models' performance. There was an obvious bias of over-prediction for dominant categories like nevus whereas there were significant problems with lowly represented group's identification accuracy as well. Melanoma is still highly significant clinically due to its malignancy nature. The model correctly classified 138 melanoma images but confused several cases with visually similar lesion categories. This difficulty is due to overlapping visual features of some dermatological diseases where differences in pigmentation, borders, and lesion structure may be subtle even during expert clinical examination. The results indicate that we should consider techniques like stratified sample selection, weight classes for samples; increase data set size & use a method called 'transfer learning'.

G. Web-Based Application Deployment

Apart from assessing models, we also incorporated our learnt CNN on an online platform for demonstration purposes of its applicability. Resnet50 model is trained and run with streamlit to create a web application that accepts dermoscopy image uploads for prediction generation which can be accessed via this link https://skin-cancer-mts8hlp57ybyikxxxay9un.streamlit.app/ . This software enables uploading of facial lesions as jpg, jpeg and png. The uploaded image is automatically resized to 224 × 224 pixels, converted to a tensor, and fed to the trained CNN model for classification. Then, this forecasted illness type will be shown on your app screen.

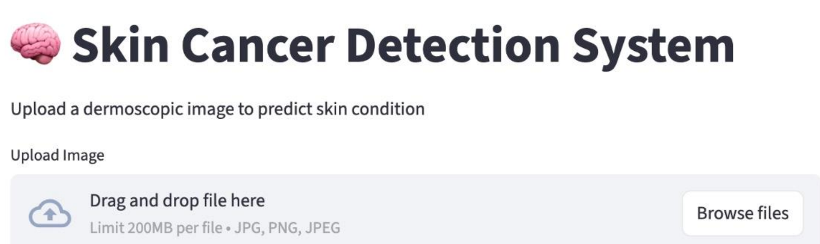

Figure 1: Landing Page of the Skin Cancer Detection System Streamlit Application Showing the Image Upload Interface.

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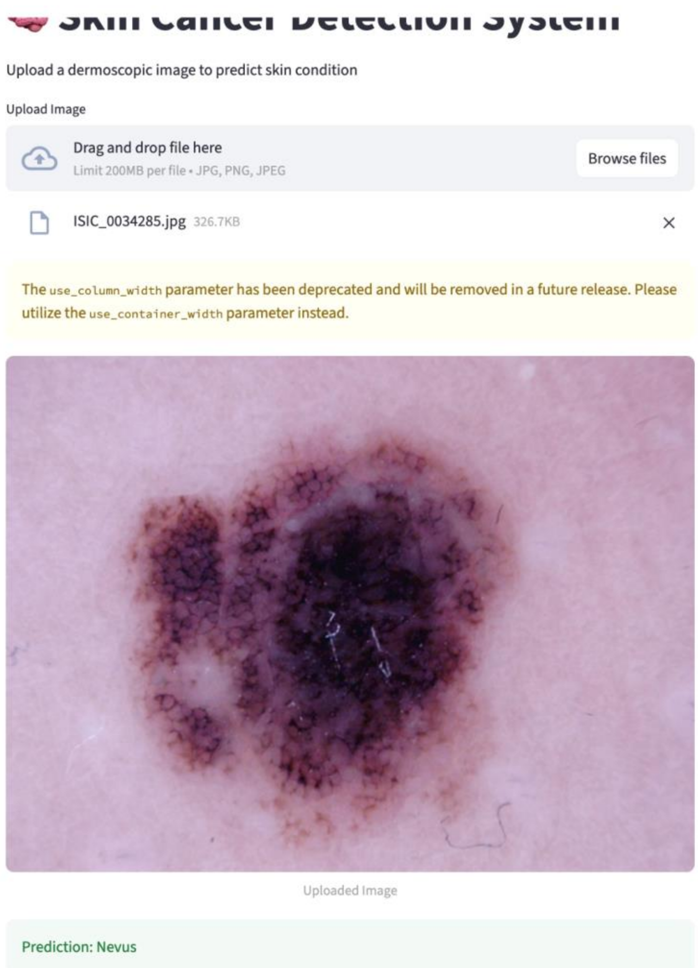

Figure 2: Deployed Application Correctly Predicting Nevus for ISIC_0034285.jpg.

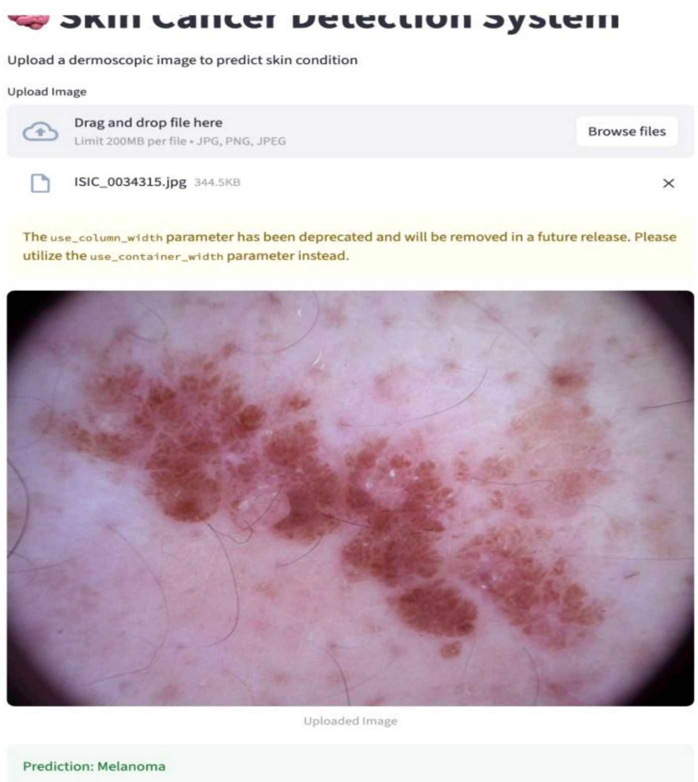

Figure 3: Deployed Application Correctly Predicting Melanoma for ISIC_0034315.jpg.

Deployment is an important aspect that was developed by us as it's one of those areas where most current AI based dermatologist researches concentrate more towards developing algorithms rather than deploying them out for use. This created framework thus closes a gap of experimentation with advanced deep learning studies to real life health care applications. The software does not substitute dermatologists but serves as an input that can help them when they are unable get proper care from specialists due to lack thereof.

H. Comparative Analysis with Previous Studies

The performance and practical contribution of the developed system were compared with existing AI-based dermatology solutions.

Table 7: Comparative Analysis of Related AI-Based Skin Disease Systems

Study	Approach	Major Contribution	Limitation
Pangti et al. (2021)	Mobile-based ML system	Supported remote dermatology diagnosis	Required improvement in accuracy and coverage
Oztel et al. (2023)	Deep learning mobile application	Achieved mobile deployment with CNN models	Dataset diversity remained limited

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Ghanta Sai Krishna et al. (2023)	Vision Transformer + GAN	Improved handling of class imbalance	Higher computational requirements
Zhou et al. (2023)	Visual Large Language Model	Combined image recognition with explanation	Requires large-scale resources
Present Study	ResNet50 CNN + Streamlit Web Application	Combines CNN classification with accessible web deployment	Requires future optimization for minority classes

As compared to other methods this approach focuses on moving away from designing models towards implementation thereof. Although there are new types of transformers as well multimodality models that have great power but need a lot computing power to work efficiently. Currently, the system prioritizes accessibility by implementing a CNN-based architecture within a lightweight web environment suitable for broader adoption.

V. CONCLUSION

The research created a CNN based website to classify skin diseases automatically from dermoscopy images. This study focused on addressing a growing demand for affordable AI-powered diagnostics that can help detect skin diseases at an earlier stage when they are more accessible through professional medical care facilities. The research showed that by combining DL based image categorization technology and web platform for deploying it we can convert computer programs to health care apps easily. The developed system used the HAM10000 dataset of 10,015 dermoscopy images from seven skin disease types. The code for a resnet50 based CNN model with image pre-processing, data augmentation, model training, performance evaluation, and deployment is included here. The experimental results indicated a classification accuracy rate of 68.22 % for the model, with weighted precision, recall, and F1-score scores of 56.25 %, 68.22 %, and 61.47 %, respectively. The results show that cnn based algorithms can recognize important features out-of-the-box on skin diseases pictures automatically. The class-level evaluation showed that the model performed well at identifying the most common Nevus type with an F1-score of 0.84, while minority classes had lower predictive performance due to data imbalances. It is an important issue of clinical imaging categorization with imbalanced diseases affecting models' robustness as well their validity. These results highlight a need for more diverse data sets; better algorithms to optimize them as well as newer methods during machine learning processes on skin care applications are essential areas that should be addressed soon. One significant aspect that was developed by us here are our trained CNN models which have been integrated with streamlets for uploading patient's skin samples getting automatic classifications from them easily accessible on-line. In contrast with other methods that are focused on developing an experimental model of DL-based health care applications; our work provides a viable strategy towards implementing such systems at patients' end. Though this model is an excellent start to AI-based skin evaluation it needs some work prior being adopted clinically. The future research must include bigger data sets, use of transfer learning as well as balancing classes for better accuracy is also needed. Improving this would increase accuracy rates for diagnoses made by AI; it would also enhance credibility with patients who are diagnosed through such methods as well.

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