



Performance and Accuracy Enhancement During Skin Disease Detection in Deep Learning

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Abstract: Epidermolysis bullosa is a type of skin cancer that is consistently ranked as among the worst diseases in the world. Accurate categorization of skin lesions in their early stages may assist during clinical deliberation, hence increasing the possibility of a cure before cancer starts. The components that are often affected by direct sunlight are the ones most likely to acquire a form of skin cancer. These include the head, and body parts that are more obvious in men than women are the legs and feet. However, it can also develop on parts of your body that are rarely subjected to air and light, such as your hands and feet. Researchers today are thinking about using deep learning to identify skin cancer more quickly and accurately. Compression operations have been performed to boost performance, while a hybrid deep learning model has enhanced accuracy metrics like recall, precision, and f1-score.

Introduction

Skin cancer is among the world's worst illnesses. Clinical decision-making might be aided by a correct early skin lesion classification, increasing the likelihood of a successful cancer treatment plan. Sun-exposed zones as varied as the head, mouth, ears, neck, chest, limbs, and feet (in women) are the most likely to acquire skin cancer. However, it can also appear in locations that are rarely exposed to air and light, such as the hands and feet. People of all skin tones are susceptible to developing skin cancer. The palms and feet soles and other areas of the body that rarely experience sunlight are particularly at risk for developing melanoma in those with darker skin tones. Cancer of the skin, an unnatural expansion of skin cells, is more common in skin that has been in the sun for a long time. This common malignancy, however, is not limited to developing in apparent places. However, it's essential to differentiate between basal and squamous cell carcinomas—also, the most lethal of all skin cancers—Melanoma. Sunlight exposure is linked to an increased risk of skin cancer. Regular self-examinations can help find skin cancer in its initial stages when it is most treatable.

The key to adequately treating skin cancer is detecting it early. This research uses a CNN classifier with a picture classification using deep learning methods. A hybrid approach was developed in the present research to improve the precision of existing skin cancer detection models. In addition, an image-compression method was used to reduce the massive dataset.

In the realm of skin disease detection using deep learning, several key challenges are prominent. One of the most significant is the variability in data, including variations in skin tones, lesion characteristics, and image quality, which can impede the learning process of the models. Another challenge is a class imbalance in datasets, where certain skin conditions are underrepresented, potentially leading to biased diagnostic models. A critical issue is the difficulty differentiating between diseases with similar visual appearances, requiring advanced pattern recognition capabilities in the models. Lastly, accurately annotating and labelling skin disease images, essential for training effective models, is time-consuming and requires expert dermatological knowledge, posing a significant challenge.

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Addressing these challenges is crucial for achieving the primary goals in this field. These include enhancing the accuracy and reliability of deep learning models for more objective and consistent skin disease diagnoses, enabling early detection and intervention, particularly for conditions like skin cancer, and automating the diagnostic process for more efficient and faster disease identification. By overcoming these obstacles and realizing these objectives, deep learning has the potential to transform dermatology, making skin disease detection more accessible, accurate, and efficient.

There are several research studies on skin cancer, some of which are presented and discussed in this section.

Hoshyar et al. (2014) focused on comparing effective methods for systemic preprocessing for skin cancer identification. When it comes to processing medical images, one of the most challenging things is the automatic diagnosis of skin cancer. It aids doctors in deciding whether a melanoma on the skin is cancerous. Therefore, scientists must figure out how to identify mistakes more effectively. The initial step in the detection process is called preprocessing, and it involves cleaning up the skin photos by removing any extraneous objects or noise in the background. This work aimed to compile information on the various preprocessing methods applicable to skin cancer pictures. This article is a solid starting point for researchers interested in developing automated methods for detecting skin cancer.

Berseth et al. (2017) researched Skin Lesions with the Hope of Spotting Melanoma. Our method completed the ISIC 2017 challenge tasks of lesion segmentation and lesion classification. Both methods employ deep convolutional networks to solve the problem set for the competition.

Ramachandram et al. (2017) reviewed the Semantic Clusters analysis in Skin Lesions using Segmental Lesion, a Convolutional neural network with deep layers. An approach to segmenting skin lesions is presented in anticipation of the ISIC Segmentation Competition for Skin Lesions, 2017. A completely CNN architecture, trained entirely on a tiny dataset, helps them achieve this goal. Our semantic segmentation architecture uses multiple methods, including I subpixel CNN and (ii) I used aortic convolutions to broaden the network's sensitivity without adding further parameters. Based on the organizer-supplied validation set, they got an IOU score of 0.642.

Yamashita et al. (2018) provided CNN in radiology: a brief introduction. The field of radiology is only one of several that were interested in CNNs, a kind of artificial neural network that has quickly risen to the top of many

computer vision tasks. By combining numerous layers of processing, including layers for convolution, layers for pooling, and layers for fully connecting, using back propagation, CNN was able to learn geographical data hierarchies automatically and adaptively. This review article summarizes the core concepts of CNN, discusses their current limitations and potential in radiology, and offers some examples of their actual use. In addition, this post will talk about two problems associated with using CNN for radiological tasks: a small dataset and poor image quality. The risk of overfitting and providing solutions to these problems. In order to maximize CNN's use in diagnostic radiology and, by extension, improve the efficiency and quality of treatment provided by radiologists, it was crucial to have a firm grasp of the technology's fundamental principles, benefits, and drawbacks.

Li et al. (2018) looked at melanoma detection by analysis of skin lesions using DNN visual similarities, low contrast between melanoma tumours and surrounding skin, and other factors all contribute to making the correct diagnosis of Melanoma very difficult. So, accurate and efficient pathologists may benefit significantly from trustworthy automated identification of skin cancers. In order to address three major issues, they describe two deep learning algorithms in this research where image analysis for skin lesions: job 1 is segmenting the lesion; task 2 is isolating the lesions using dermoscopy characteristics; and task 3 is classifying the lesions. We present a deep learning system comprising two FCNNs to generate both the segmentation and the coarse classification results at once. The distance heat map was created using a LICU designed to improve the coarse classification findings. For dermoscopy feature extraction, a basic convolutional neural network was presented. The ISIC 2017 dataset served as the basis for testing the suggested DL frameworks. Accuracy levels of 0.753 on Task 1, 0.848 on Task 2, and 0.912 on Task 3 were attained in our experiments, demonstrating the potential of our frameworks.

Yu et al. (2019) recognized Melanoma spotted on dermoscopy automatically using an intense residual network. Through very deep CNNs, our much deeper networks could amass more varied and discernible characteristics for further precise recognition than with earlier methods using either simple, handcrafted features or shallower, pre-existing CNNs. We present a series of techniques to guarantee efficient training and learning under constrained training data, allowing intense networks to realize their full potential. They use residual learning to mitigate degradation and overfitting issues as a network's

depth increases. With this method, they can be sure that the performance gains due to deeper networks are realized. Next, they employ a multi-scale contextual information integration technique to enhance the performance of an FCRN they construct for accurate skin lesion segmentation. Combining the suggested FCRN with other intense residual networks establishes a two-stage framework (for classification). Using segmented findings rather than whole dermoscopy images, this method allows better features for the classification network to use in making predictions.

Yanase et al. (2019) introduced computer-aided diagnosis in medicine: seven significant obstacles. Doctors may benefit from CAD since it helps them make more informed diagnoses in less time. In several fields of medicine, CAD systems are now indispensable. Furthermore, it is one of the well-established research areas at the convergence of the biomedical and IT disciplines. However, CAD systems continue to struggle with a few major issues. This article discusses seven problems stemming from technological infrastructure deficiencies at the intersection of healthcare and computing. These difficulties originate from issues with patient data, resistance to change among medical practitioners, insufficient guidelines and standards in many areas of CAD, and other related issues. Some recent research advancements in the direction of these issues are also described in this study. The research and development pillars necessary to take CAD to the next level rest on how well these seven critical problems were met. To do this, researchers and medical professionals in computer science and medicine would need to work together in even closer coordination. Yuan et al. (2019) focused on the optimization of convolutional and deconvolutional networks for dermoscopy image segmentation. To enhance the sensitivity of discrimination in our earlier work, we have developed a more in-depth network design with smaller kernels herein in the study. Further improvements in segmentation performance were achieved by including color data from several sources color spaces during network training. They completed and evaluated our approach thoroughly at the 2017ISBI skin lesion segmentation challenge. Our technique outperformed the other 20 finalists in the competition by a wide margin. Jaccard Indexes averaged 0.765 on the 600 test pictures used for evaluation after training on the complete set of 2000 challenge training photos.

Fu'adah et al. (2020) presented the development of an automatic method for Staging Skin Cancer using the CNN. The established technique in this study uses a CNN to identify skin cancer from benign tumor lesions routinely.

The proposed model features three cloaking levels, each corresponding to a different-sized output channel (16, 32, and 64). SGD, RMSprop, Adam, and Nadam are only a few optimizers used in the proposed model, each with a learning rate of 0.001. The ISIC dataset divides skin lesions into four categories: skin tumours and birthmarks (nevi), squamous cell carcinoma, and Melanoma. Adam optimizer achieves the most significant result, with an accuracy value of 99%. The outcomes are superior to those of the current skin cancer categorization method.

Manzoor et al. (2021) detected skin lesions with minimal overhead by using the most promising features fusion. Due to their similarities, multiclass skin disease photos were previously unidentifiable using existing methods. The suggested research presents a computer-assisted framework for the automated identification of skin diseases. This study gathered and standardized records from two databases based on six prevalent skin diseases: BCC, AK, SK, N, SCC and M. Furthermore, deep CNN are used to carry out the segmentation. Additionally, Characteristics are taken from the cuts in the skin using the Features, GLCM, and the ABCD rule. They employ Alex Net transfer learning to extract deep features and they use a SVM for classification. The experimental findings demonstrate that SVM outperforms previous studies in terms of accuracy, with 100% accuracy for AK illness, 92.7% accuracy for BCC, 95.1% accuracy for M, 97.8% accuracy for N, 93.0% accuracy for SK, and 91.4% accuracy for SCC.

Usmani et al. (2021) automated skin lesion detection method using reinforcement learning. The suggested lesion segmentation approach was a Markov decision procedure. A deep reinforcement-learning technique was used to teach an agent how to divide the area. Similar to how doctors define a region of interest, our approach involves drawing a boundary around the area of interest. In order to define an area, the agent performs a series of sequential actions.

Moreover, action space is defined by a collection of continuous parameters. The segmentation model was trained with a deep deterministic policy gradient in a continuous action space technique. They see steady performance gains as they refine our segmentation findings using the suggested strategy. Finally, they test our proposed model on the 2017 images from the ISIC and the Human vs. Machine (HAM10000) and PH2 datasets. Accuracy for naevi was 96.33%, Melanoma was 95.39%, and seborrheic keratosis was 94.27% using the ISIC 2017 dataset. Other measures were used to rank these datasets, and they all performed better than the current gold standard lesion segmentation technique.

Panja et al. (2021) provided a Keras and TensorFlow-based method for identifying skin cancer. Skin cancer is an alarming disease that threatens humans. The necessity for early identification of skin cancer has increased as a result of the disease's expensive treatment costs and high fatality rate. Recently, advances in image preprocessing and machine learning have made it possible to apply such methods to detect skin cancer. Media outlets like CNN were one successful strategy. After dermoscopy images have been segmented, a feature extraction method is used to determine what features of the injured skin are present. Cells. To better identify skin cancer and distinguish between malignant (Melanoma) and benign cases, they present a CNN model (non-malignant). Layers in the model's design facilitate machine data interpretation. In these situations, one can always count on accurate outcomes. They were using a human process rather than an automated one to avoid making any mistakes.

Alsaade et al. (2021) reviewed using AI algorithms to build a skin lesion recognition system for diagnosing Melanoma. The suggested system was built utilizing novel DL algorithms and more conventional AI machine-learning techniques. Dermoscopy pictures from PH2 and ISIC 2018 were gathered for this analysis of the diagnostic process. Separate components, feature-based and deep learning, make up the final product. The techniques for extracting features were the basis for creating the feature-based system. The active contour approach was devised to segment the lesion using dermoscopy pictures. Texture characteristics were extracted from these skin lesions using GLCM techniques and ANNs, which were then used to process the collected features. In the second setup, CNN technology was implemented to classify skin illnesses efficiently. The massive Alex Net and ResNet50 transfer learning models were used to pretrain the CNNs. Experiments demonstrated for both State-of-the-art approaches were bested by the suggested strategy on the HP2 and ISIC 2018 datasets. The two proposed systems were evaluated based on a number of performance indicators, including accuracy, specificity, sensitivity, precision, recall, and F-score. The ANN model outperformed the PH2 (97.50%) and ISIC 2018 CNN (98.35%) models. Analyses, comparisons, and suggested melanoma categorization and detection systems methods are presented.

Banerjee et al. (2021) introduced neuromorphic and deep learning for melanoma lesion diagnosis. The paper's most notable feature was its use based on the concept of a triangular neuromorphic number with unspecified parameters and the subdivision obtained by the termination of relocating a succession of points in a

straight line. We found encouraging outcomes from our study, which included 40,676 photos culled from four open-source datasets (ISBI 2017, ISIC 2018, ISIC 2019, and ISIC 2020). Its Jac score on the ISIC 2020 dataset was 86.81. percent, on the ISBI 2017 dataset, it had a score of 95.98 percent. On the ISIC 2018 dataset, it had a score of 95.66 percent; on the ISIC 2019 dataset, it had a score of 94.42. When compared to previously established parameters for comparable efforts in this sector, the results of the current study were, in most cases, nothing short of spectacular.

Shawon et al. (2021) predicted the likelihood of skin cancer, and a CNN-based computer-assisted skin cancer diagnostic system has been shown. Images were acquired, processed, segmented, features extracted, and then classified in our proposed five-step approach. The photos are first dulled to eliminate any visible noise, then smoothed using a median filter. After that, the photos were cleaned up to classify them using the k-means method. Images were segmented before being fed for input into a convolutional neural network (CNN) example of feature separating apart and labeling. The standard method for classifying thermographic divided into healthy and diseased picture kinds has an accuracy of 80.47 percent. We compare our skin cancer detection system's performance to that of different models, such as ANN, KNN, and RF, as they are developed. Our proposed method accurately differentiated between noncancerous and cancerous skin growth using the "ISIC Challenge 2016" test dataset with an accuracy rate of 80.47 percent.

Acosta et al. (2021) focused on DL for melanoma detection in dermoscopy pictures. Over the last 30 years, Melanoma has grown more common, and early identification was a key element in lowering death rates. As a result, it is helpful to have access to an automated, trustworthy system that skin lesions and/or changes in skin pigmentation (dermoscopy) can confirm the presence of Melanoma. Results obtained with the proposed model imply a significant improvement in performance over state-of-the-art skin lesion classifiers compared to those obtained with the latest and greatest alone.

Cabanac et al. (2021) looked CNN and SVM for identifying skin Cancer. They searched scholarly works for twisted language and zeroed down on a single reputed publication where such terms were often used. They tested a detector on the abstracts of recently published papers in this journal as well as multiple control sets, with the hypothesis that sophisticated language models were being used. The pairwise comparisons show a high concentration of abstracts in the journal that have been marked as synthetic. In addition, they call attention to anomalies in

its functioning, such as sudden shifts in editorial schedules. They back up our need for inquiry by dissecting many suspect publications and highlighting their most troubling characteristics, such as their convoluted writing style, citing of nonexistent literature, and unacknowledged picture reuse. Surprisingly, there are websites out there that can rewrite your content for free while producing twisted prose. Some writers padded their works with reworked passages. They want to bring attention to papers that may include problematic artificial intelligence-generated or revised content that was able to go through peer review. Falsified texts pose a danger to the credibility of scientific studies.

Kotra et al. (2021) provided a classification of dermoscopy images using a CNN supplemented by manually developed characteristics. Dermoscopy pictures used in this study were sourced from the 2016 edition of the repository of skin images worldwide (ISIC 2016). The proposed method enhances the accuracy of other state-of-the-art methods for identifying Melanoma and other skin lesion classifications by using a Convolutional Neural Network (CNN) to analyze and classify dermoscopy images, with the manually crafted features of a dermoscopy image using a Scattered Wavelet Transform as additional input to a fully connected layer of CNN. A convolutional neural network is used in the proposed method. (CNN) to improve upon the quality of a raw dermoscopy image. 98.13% accuracy rate for the identification of Melanoma, a 93.143% rate for the classification of Melanoma versus Nevus, a 95.4% rate for the classification of Seborrheic Keratosis versus Squamous Cell Carcinoma, and a 96.873% rate for the classification of Mel (BCC).

Khan et al. (2021) used multiclass-enhanced moth-flame optimization for deep learning-based lesion segmentation. We offer a fully automated method for identifying and categorising skin lesions across many classes by leveraging the most discriminative deep characteristics. To begin, the source pictures were improved using colour-managed Values of the histogram's intensity (LCcHIV). Then, a new Deep Saliency Segmentation technique is used to measure saliency by training a ten-layer neural network using convolutions (CNN). The thresholding process converts the created heat map into a binary representation. In order to extract features from the colour lesion images, a pre-trained, deep CNN model was used. They used a technique called improved moth flame optimization (IMFO) to zero in on the most important characteristics while avoiding high-dimensionality traps. Multiset maximum correlation analysis (MMCA) was used to integrate the features

generated and Labels were applied using a classifier called the Kernel Extreme Learning Machine (KELM). For instance, on the ISBI 2016 dataset, the proposed technique achieves 95.38 percent accuracy in segmentation, on the ISBI 2017 dataset, it achieves 95.79 percent, on the ISIC 2018 dataset, it achieves 92.69 percent and on the PH2 dataset, it achieves 98.70 percent. The HAM10000 dataset is used to evaluate classification accuracy. Where it was shown to have reached an accuracy of 90.67%, they contrast it with the current best practises to demonstrate the efficacy of the suggested strategies.

Alf et al. (2022) Melanoma Skin Cancer Diagnosis Without Surgery That Can Be Interpreted Applying Machine Learning Model Ensemble Stacking with Deep Learning. In this paper, they provide a DL machine learning model stacking ensembles approach to the non-surgical diagnosis of Melanoma. The classifier models are trained using a dataset that consists of images of both normal and malignant moles on the skin. The automated study foundational models were trained using handcrafted features. Level one model stacking was trained by cross-validating predictions from these foundational models using the training data. Transfer learning was performed using pre-trained deep learning models that were fed ImageNet data. For every model, the classifier was rated. After that, the deep learning models were evaluated using an ensemble of models. "In addition, an interpretability method is built using shapely adaptive explanations, which creates heat maps to highlight regions of a picture most indicative of the disease. Because of this, our model's findings may now be understood by dermatologists. They found the most effective model for skin lesion classification by calculating accuracy, F1-score, Cohen's kappa, confusion matrix, and ROC curves.

Research Gaps Identified

The research gaps in the field of skin disease detection using deep learning, as identified from various studies include:

Handling Large and Diverse Datasets: Many existing models struggle with efficiently processing and learning from extensive and diverse datasets, which is crucial for accurate skin disease detection.

Generalizability Across Different Skin Types: There is a need for models that can generalize effectively across various skin types, particularly in accurately diagnosing skin diseases in darker skin tones.

Table 1. Related research works.

Sl. No..	Author/Year	Title	Methodology	Limitation
1	Hoshyar et al. (2014)	The beneficial techniques in the preprocessing step of skin cancer detection systems were compared.	Skin cancer	The scope of work is limited
2	Berseth (2017)	ISIC 2017 - Skin Lesion Analysis Towards Melanoma Detection	Skin Lesion	No work is done in the direction of security
3	Ramachandram and DeVries (2017)	LesionSeg: Semantic segmentation of skin lesions using Deep Convolutional Neural Network.	Deep Learning, CNN, skin lesions	There is not performed in the future.
4	Yamashita et al. (2018)	Convolutional neural networks: an overview and application in radiology	CNN	Lack of efficiency
5	Li and Shen (2018)	Skin lesion analysis towards melanoma detection using deep learning network	Skin lesion, deep learning network	Need to improve the performance and accuracy
6	Yuan and Lo (2019)	Automated Melanoma Recognition in Dermoscopy Images via Very Deep Residual Networks	Dermoscopy Melanoma Recognition	There is a lack of performance
7	Yanase and Triantaphyllou (2019)	The seven key challenges for the future of computer-aided diagnosis in medicine.	computer-aided diagnosis	Research is limited to traffic flow
8	Yuan and Lo (2019)	Improving Dermoscopic Image Segmentation with Enhanced Convolutional-Deconvolutional Networks	Dermoscopic Image	There is less technical work
9	Fu'adah et al. (2020)	Convolutional Neural Network (CNN) for Automatic Skin Cancer Classification System	CNN, Skin Cancer	Lack of security and accuracy
10	Manzoor et al. (2022)	A lightweight approach for skin lesion detection through optimal feature fusion	Skin lesion	There is a lack of performance
11	Usmani et al. (2021)	A reinforcement learning algorithm for automated detection of skin lesions.	Skin lesions	Lack of technical work
12	Panja et al. (2021)	An Approach to Skin Cancer Detection using Keras and Tensorflow.	Skin Cancer	The performance of this research is very low.
13	Alsaade et al. (2021)	Developing a Recognition System for Diagnosing Melanoma Skin Lesions Using Artificial Intelligence Algorithms.	Skin Lesions, Artificial Intelligence	Did not consider a real-life solution

14	Banerjee et al. (2021)	Diagnosis of melanoma lesion using neutrosophic and deep learning	Deep learning, Melanoma lesion	Need to consider optimization technique
15	Shawon et al. (2021)	Identification of risk of occurring skin cancer (Melanoma) using convolutional neural network (CNN).	Skin cancer, CNN	Need to enhance the scope of work
16	Acosta et al. (2021)	Melanoma diagnosis using deep learning techniques on dermatoscopic images.	Deep learning, Melanoma diagnosis	Need to do more work on accuracy
17	Cabanac et al. (2021)	Tortured phrases: A dubious writing style emerging in science.	Dubious writing	Lack of flexibility
18	Kotra et al. (2021)	Dermoscopic image classification using CNN with Handcrafted features.	Dermoscopic image, CNN	There is a lack of technical work
19	Khan et al. (2021)	Skin lesion segmentation and multiclass classification using deep learning features and improved moth flame optimization.	Skin lesion segmentation, deep learning	There is a lack of security, scalability
20	Alf et al. (2022)	A Non-Invasive Interpretable Diagnosis of Melanoma Skin Cancer Using Deep Learning and Ensemble Stacking of Machine Learning Models”.	Deep learning, Machine Learning, Skin Cancer	This work is not long-lasting work

Table 2. Strengths and Weaknesses of Different Approaches.

Approach	Strengths	Weaknesses
Conventional CNN Models	Effective in image recognition and classification. Good at identifying patterns in skin images.	Limited efficiency with large datasets. May struggle with accuracy in differentiating similar lesions.
ResNet50 Models	Capable of deep learning with many layers, improving feature extraction. Addresses the vanishing gradient problem.	Computationally intensive. It is challenging to train on extensive datasets.
Hybrid Models (CNN + ResNet50)	Combines the benefits of CNNs and ResNet50 for improved accuracy. Better handling of complex data patterns.	Complex implementation. Requires substantial computational resources.
Image Compression Techniques	Efficient management of large datasets. Reduces training and testing time.	Potential loss of crucial image details impacting disease detection accuracy.

Differentiating Between Similar Conditions: Current models' ability to distinguish skin disorders with similar visual characteristics is severely lacking. Balancing Computational Efficiency and Accuracy: Many high-

photos as the ResNet50 model. It was developed as part of this research project. Even while earlier studies used the Conventional CNN model, the researchers didn't pay much attention to how to improve the models' overall

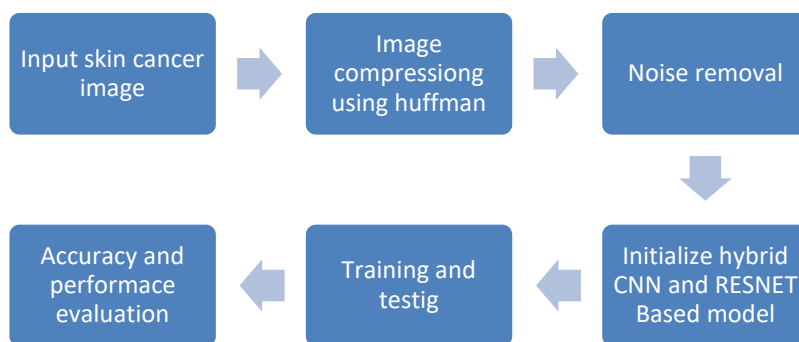


Figure 1. Process flow of proposed work.

accuracy models are computationally intensive, making them less feasible for practical use, especially in resource-constrained settings.

Integration with Clinical Workflows: Developing models that can be seamlessly integrated into existing clinical workflows and medical systems is a challenge that needs more attention.

Problem Statement

There is different research in the area of skin cancer detection, but the issue with conventional research work is the lack of performance and accuracy. The chosen research gap addresses Handling Large and Diverse Datasets and Balancing Computational Efficiency and Accuracy. There is a need to compress the image to reduce the size of the image set. It could help in training and testing time reduction. Moreover, image quality needs to be improved to improve accuracy. Moreover, the hybrid model can also improve performance and quality.

Proposed Work

In the work that has been presented, the current model provides a training phase in which a dataset for skin cancer detection is considered for training. The dataset is being pre-processed to resize the photos and compress those images using the Huffman technique. This step takes place before the actual processing begins. Following preprocessing, a suggested hybrid model that considers both the CNN model and the Resnet50 model is used to provide a more accurate result.

Within the scope of this study, we investigated two distinct CNN models to determine which one would be superior when it came to classifying photos depicting skin cancer. In the end, we successfully trained a CNN, which allowed us to obtain accurate predictions. We refer to the hybrid model we developed for classifying skin cancer

performance. Although these studies contributed to an increase in accuracy, there is still potential for development in how rapidly training, testing, and validation can be completed.

Results and Discussion

Image sets of malignant and healthy images have been obtained from Kaggle, and Training of 5000 skin cancer images has been made using the proposed model. Images used during training are shown below.

After training, a testing operation was made to obtain the confusion matrix, shown in the following section.

Accuracy of DL during classification of skin cancer images

The present section is focused on deep learning of the proposed work, where a confusion matrix has been obtained after testing.

Results

TP: 1990

Overall Accuracy: 99.5%

Table 3. Confusion matrix of proposed work

	Malignant	Healthy
Malignant	995	5
Healthy	5	995

Table 4. Accuracy in the case of the proposed model

Sl. No.	Accuracy	Precision	Recall	F1 Score
1	99.5%	0.99	0.99	0.99
2	99.5%	0.99	0.99	0.99

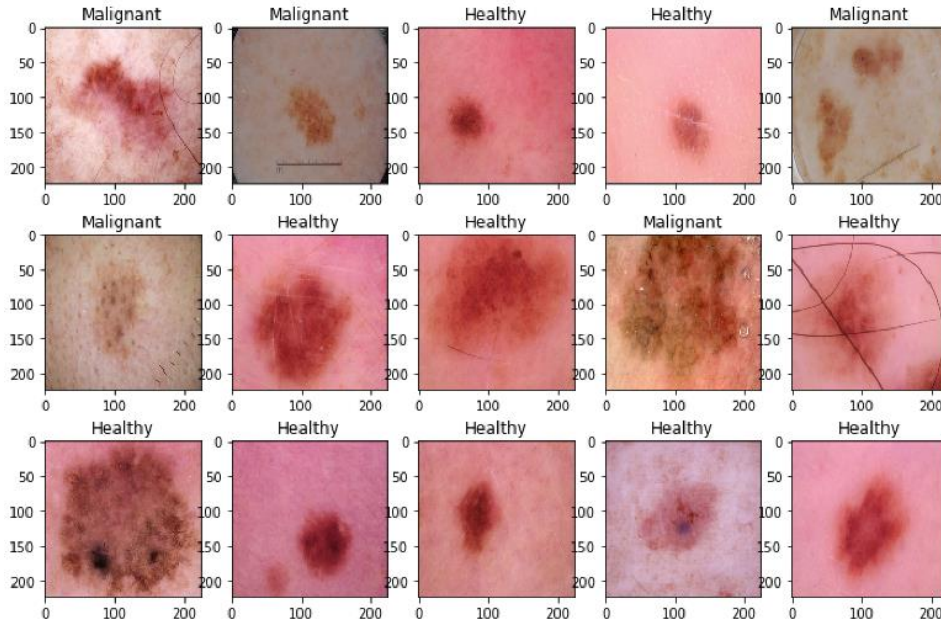


Figure 2. Skin cancer images

Source: Kaggle Dataset for Skin Cancer Detection (Retrieved in 2023)

Table 5. Comparison of Accuracy parameters

Models	Accuracy	Recall	F1-Score	Validation_Accuracy	Test_Accuracy
CNN	96%	89.5%	91.76%	87.34%	89.5%
Proposed model	99.5%	99%	99%	99.5%	99.5%

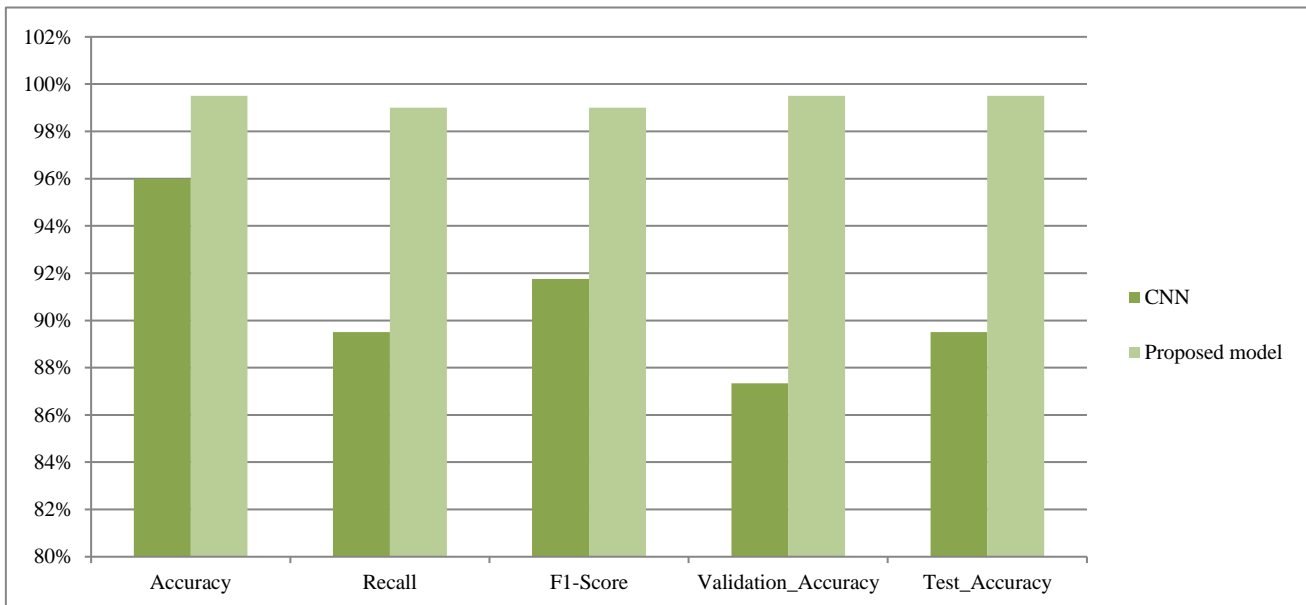


Figure 3. Comparison of proposed work to conventional

Table 6. Comparison of Training Time

Epoch	Conventional CNN	Proposed model
1	0.286332	0.230715
2	0.953987	0.889832
3	0.819987	0.808038
4	0.284532	0.249384
5	0.592238	0.559098
6	0.2034	0.166699
7	0.648808	0.569103
8	0.251348	0.222636
9	0.05322	0.018981
10	0.6486	0.555053
11	0.389581	0.306448
12	0.097889	0.044841
13	0.798598	0.782611
14	0.84602	0.79535
15	0.085801	0.026842
16	0.495166	0.465199
17	0.613617	0.531414
18	0.367073	0.31623
19	0.949321	0.910476
20	0.709134	0.641416
21	0.924655	0.840586
22	0.357879	0.340234
23	0.56195	0.541416
24	0.947286	0.894106
25	0.732073	0.695273

5, training time has been shown as follows-

Comparison of Accuracy Parameter

The following table is presenting the accuracy of the proposed and conventional model considering recall, f1-score

Performance of deep learning model during skin cancer detection

Training operation has been made considering 25 epochs. In the case of each epoch, the training time has been calculated and shown in Table 5. Considering Table

Discussion

The research presented in this paper marks a significant advancement in applying deep learning techniques for skin disease detection, particularly skin cancer. The study addresses the inherent challenges in skin cancer detection by integrating a hybrid model combining Convolutional Neural Networks (CNNs) and ResNet50. It paves the way for more nuanced and effective diagnosis strategies.

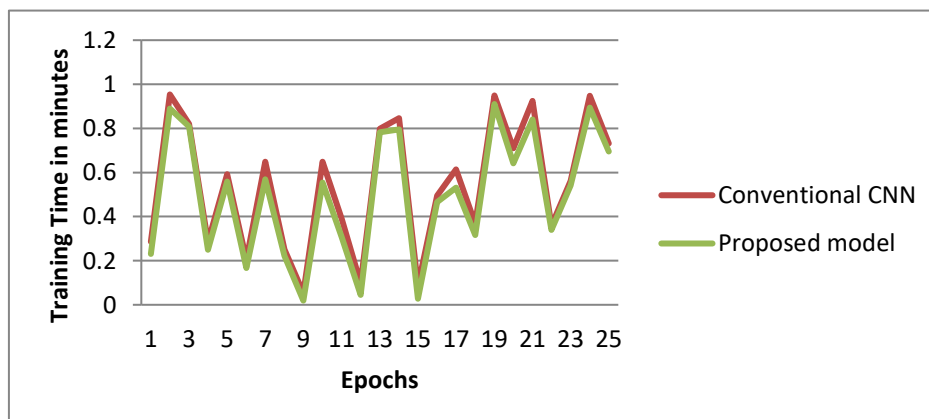


Figure 4. Comparison of Training Time

Contextualization within the Field:

The integration of CNNs with ResNet50 is particularly noteworthy, as it leverages the strengths of both techniques. CNNs are renowned for their efficacy in image recognition and classification, crucial in identifying subtle patterns in skin lesions. ResNet50, with its deep residual learning framework, aids in solving the vanishing gradient problem, allowing the network to learn from many layers without a decline in performance. This integration aligns with the current trend in medical image analysis, which increasingly relies on deep learning for its accuracy and efficiency.

Addressing Challenges:

The proposed model demonstrates exceptional competence in dealing with the variability of skin cancer appearances, a notable challenge in dermatology. By achieving a high accuracy rate, the model underlines the potential of machine learning in enhancing diagnostic accuracy, especially for early-stage cancers. This is particularly crucial given the varied manifestations of skin cancer across different skin tones, a factor that has historically complicated diagnosis.

Limitations and Considerations:

While the results are promising, it is essential to acknowledge the study's limitations. The model's performance in real-world clinical settings, where data can be more heterogeneous and noisier, is yet to be evaluated. Additionally, the training dataset's diversity, particularly in representing various skin types, must be considered to ensure the model's applicability across a broad demographic spectrum.

Future Directions:

Future research could enhance the model's robustness by incorporating a more diverse dataset that includes a wide range of skin types and conditions. This would improve the model's generalizability and its utility in global healthcare settings. Furthermore, integrating the model with real-time diagnostic tools and mobile applications could revolutionize how skin diseases are detected and managed, especially in remote or under-resourced areas.

Conclusion

Considering the above simulation, it is concluded that the proposed work provides better accuracy and high performance. Image compression has improved its performance, whereas noise removal and hybrid approach used in research has improved the accuracy parameters such as f-score, recall value, and precision.

The research undertaken in this study represents a significant step forward in dermatological diagnostics

using deep learning methodologies. The development and successful application of a hybrid model, which combines the strengths of Convolutional Neural Networks (CNNs) and ResNet50, demonstrates a notable improvement in the accuracy and performance of skin cancer detection. Achieving an overall accuracy of 99.5% is a testament to the model's efficacy and highlights the potential of advanced AI techniques in medical imaging. This integration is particularly relevant given the complexity and variability of skin cancer manifestations, making it a challenging area for accurate diagnosis.

Moreover, the study's focus on image compression and noise removal as part of the model's methodology addresses critical issues in handling large dermatological datasets. By reducing the computational load without compromising the integrity of the data, the proposed model presents a practical solution for real-world applications. This aspect of the research is crucial, as it directly contributes to the feasibility of implementing such advanced diagnostic tools in clinical settings, where resource constraints often limit the use of computationally intensive methods. However, it is essential to recognize that the transition from a controlled research environment to clinical practice involves additional challenges, including the need for extensive validation across diverse patient populations and varied clinical conditions.

Looking forward, the implications of this research are vast and transformative. As the model's efficacy in a clinical setting becomes more established, it can pave the way for early and more accurate skin cancer detection, significantly impacting patient outcomes. The potential integration of such a model into telemedicine and mobile health applications could further democratize access to advanced diagnostic tools, especially in under-resourced or remote areas. Future research should focus on enhancing the model's adaptability and robustness, ensuring it can effectively handle the variability and unpredictability of real-world clinical data. Expanding the model's training with a more diverse dataset will ensure its effectiveness across different skin types and conditions. The research thus sets a precedent for future innovations in medical imaging, highlighting the transformative role of AI in enhancing healthcare delivery and patient care.

Conflict of Interest

The author declares that there is no conflict of interest regarding the publication of this paper.

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