Grenze International Journal of Engineering and Technology, January Issue

AI Powered Tele dermatologist and Bridging Gap in Remote Health Care

Sameer Shaik[1], Dushyanth Chandu[2], Pranay Kumar Nittu[3], Abinandhan Kolanthasamy[4], Pavan Pinninti[5] and Abhishek Bhattacherjee[6]
[1-6]Department of Computer Science and Engineering, Lovely Professional University Nandyala, Andhra Pradesh, India
Email: sameer.kattubadi@gmail.com, chandudushyanth621@gmail.com, pranaykumarnittu@gmail.com, nandhanabi7@gmail.com, pinnintipavan9989@gmail.com, abhishek.27306@lpu.co.in

***Abstract*—Skin diseases are becoming a greater concern throughout the world, specifically in the remote areas where medical facilities are very scarce. Early diagnosis is particularly important for effective treatment for skin diseases. Availability of dermatologists is the major concern in distant places. The Development of AI-Powered Tele dermatologist uses Deep Learning methods for early diagnosis of different skin diseases is presented in this research. A Convolutional Neural Networks (CNN) algorithm is used in training the model to diagnose skin lesions. The ISIC 2019 dataset is used to train the model across 9 categories of skin diseases.**

***Keywords*— Deep Learning, Convolutional Neural Networks, Computer Vision, Feature Extraction, Tele-dermatology.**

I. INTRODUCTION

Artificial Intelligence has been a very revolutionizing technology in the technological fields. One of its applications is for diagnosing skin diseases using Computer Vision Technology and the algorithms of Deep Learning. The diagnosis of skin using AI can be integrated into websites and mobile applications and provide a service of remote skin diagnosis for the patients in the areas where there is a scarcity of medical facilities.
Doctors can use pictures and artificial intelligence (AI) to diagnose skin conditions.
Patients in remote locations can snap photos of their skin and submit them to a physician for evaluation. The physician can then promptly detect possible skin conditions using AI.
This can speed up diagnosis and treatment, particularly for dangerous conditions like melanoma. Furthermore, if a person's skin condition is not severe, this can also help them feel more at ease. Melanoma, melanocytic nevus, basal cell carcinoma, actinic keratosis, benign keratosis, dermatofibroma, vascular lesions, and squamous cell carcinoma are among the skin conditions that the AI has been trained to detect.
Even though the severity of these illnesses varies, everyone should receive early detection and treatment [1].
AI is used in tele-dermatology to evaluate images of skin lesions and forecast skin diseases.
Patients can use their smartphones to snap photos and email them to a physician for review. Quick diagnosis suggestions from the AI can make patients feel more at ease if their skin issue is not significant and can also help detect more serious illnesses like melanoma.
Tele-dermatology driven by AI is a significant advancement in expanding access to healthcare. AI has the potential to save lives and lower healthcare costs by assisting physicians in working more productively and identifying skin issues sooner.

Grenze ID: 01.GIJET.11.1.50_1

But there are additional issues to think about, like the AI's accuracy, protecting patient data, and the requirement that clinicians be involved in the process. The function of AI in tele-dermatology, associated difficulties, and possible effects on dermatological treatment are covered in this research. Automating the detection of skin diseases from picture data is made possible by convolutional neural networks (CNNs), a type of artificial intelligence that excels at image classification tasks [2].

By examining their visual traits from dermatoscopic pictures, CNNs may be trained to identify and categorise skin lesions including melanoma, basal cell carcinoma, actinic keratosis, and more in the context of AI- powered tele-dermatology.

Convolutional, pooling, and fully connected layers are among the layers that make up the CNN architecture. These layers cooperate to extract and interpret information from the input images. While pooling layers lower dimensionality and increase the network's computational efficiency, convolutional layers use filters to capture edges, textures, and patterns in skin lesions. CNN learns to distinguish minor variations between benign and malignant lesions by using labelled datasets of skin pictures. For instance, a well-trained CNN can recognise asymmetry, irregular boundaries, or colour differences to distinguish between benign moles (melanocytic nevi) and melanoma.

CNNs are an ideal solution for remote healthcare because they can be used on online or mobile platforms and offer quick and precise diagnostic capabilities. Even in environments with limited resources, the model can make predictions in real time by allowing patients to upload pictures of skin lesions.

The difficulties, however, lie in making sure the dataset is varied and reflects a range of skin tones and conditions, as well as in optimising the algorithm for accuracy across various demographics. CNNs, however, can greatly improve tele- dermatology by enabling early skin disease diagnosis and identification, particularly in underprivileged areas.

By improving treatment accuracy, efficiency, and accessibility, artificial intelligence (AI) is changing healthcare. AI analyses vast volumes of data using machine learning to identify trends that can aid in early disease detection and the development of individualised treatment regimens.

Radiologists can detect problems like tumours and fractures more accurately by using AI-powered tools to help them analyse medical pictures [3]. For instance, it can assist in the automation of processes by analysing patient records and extracting clinical data. Finally, AI chatbots can offer rapid support and information to patients, thereby alleviating the burden of medical practitioners. Overall, considering all these factors, AI has revolutionized medical diagnosis, improved patient outcomes, and streamlined the delivery of healthcare.

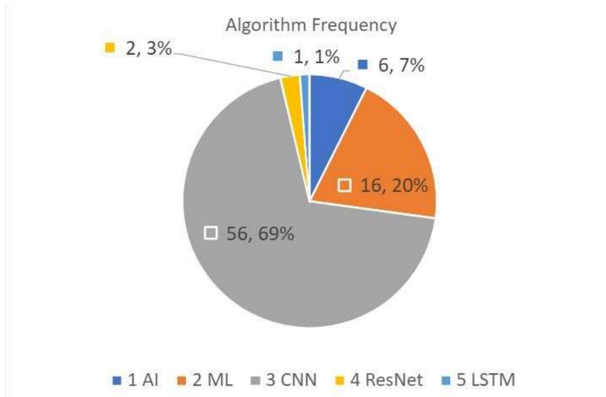
II. Literature Review

Dermatology is continuously changing due to artificial intelligence, that is generating innovative answers to the increasingly rising prevalence of skin conditions. Millions of individuals throughout the world, people suffer a lot from skin diseases like psoriasis, acne, eczema and even a few forms of skin cancer [4]. This necessitates highly advanced diagnostic tools capable of facilitate early identification, and efficient treatment is and growing with a subconscious sense of the importance of skin health [5].

TABLE 1

S. no	Name of Disease	No of Images
1	Melanoma	4522
2	Melanocytic nevus	12875
3	Basal cell carcinoma	3323
4	Actinic keratosis	867
5	Benign keratosis	2624
6	Dermatofibroma	239
7	Vascular lesion	253
8	Squamous cell carcinoma	628

In dermatology, AI is mostly applied in the classification and detection of patterns in images using techniques like CNN to analyze lesions in the skin taken from medical images [6]. This approach has processed and analysed enormous data produced by dermatological imaging technologies with considerable efficiency. The researchers want to advance patient outcomes and diagnostic accuracy by training an artificial intelligence model to distinguish between benign and malignant skin lesions. Early detection of skin cancer, for instance, can significantly increase survival rates, emphasizing the critical role of robust diagnostic systems.



In the above pie-chart the frequency of the algorithm used in the research papers is represented. Most of the papers we collected used the Convolutional Neural Networks. It is overly complex yet exceptionally reliable because of its nature of automatic feature identification and detection. So, we have decided to use the Convolutional Neural Networks to build our project.

In the context of tele-dermatology, AI can reduce the workload of dermatologists by handling routine diagnostics, allowing professionals to focus on more complex cases. This is especially beneficial in remote and underserved areas with limited access to specialists. Tele- dermatology involves patients submitting skin lesion images for analysis, which AI can enhance by providing automatic diagnostic suggestions before a dermatologist reviews the case. This can significantly reduce waiting times and improve access to care. Studies like Brinker et al. (2019) have explored the use of deep learning algorithms in tele-dermatology, demonstrating their potential to increase diagnostic efficiency while maintaining high accuracy.

[8] discussed how transfer learning can be used to extend the learnings of a model to another model with a similar problem. Our model can be extended for such a model which is developed for identifying skin diseases by analyzing the skin lesions of the patients to decrease the training time efficiently.

Despite the promise of AI in dermatology, challenges remain. One primary concern is the quality and diversity of the data sets used to train AI models. Skin tones, ethnic backgrounds, and environmental factors can influence the appearance of skin lesions, and models trained on homogeneous datasets may not generalize well to diverse populations [9]. Addressing this requires inclusive datasets that represent a wide range of skin types and conditions. Also, the quality of input photos affects how accurate AI models are. Clear instructions for taking excellent pictures with consumer-grade equipment are necessary for AI-powered tele-dermatology to be successful. Campaigns for public health can teach patients how to properly record their skin conditions, enhancing the quality of the data.

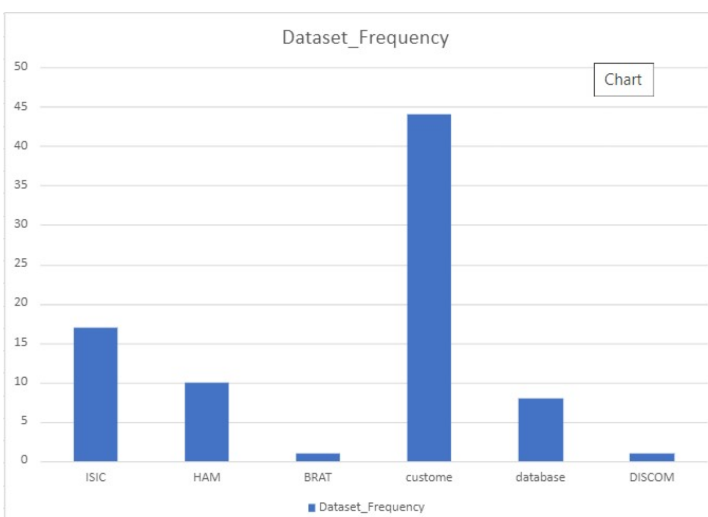


Fig 1. Datasets

The above figure of datasets represents the frequency of the usage of datasets in the research papers we have collected. Most of the research papers used the public dataset of ISIC apart from the custom datasets. So, we have decided to use the ISIC dataset as it is widely used and after looking into the dataset the data is also huge enough to train our model.

Another issue with AI models is their interpretability. Since most deep learning models function as "black boxes," it can be challenging to comprehend how they arrive at particular diagnostic conclusions [10]. Building explainable AI models can increase patient and healthcare provider trust. Dermatologists can confirm and validate AI- assisted diagnoses by using techniques like saliency maps and attention processes, which can offer insights into the decision-making process.

Additionally, ethical considerations are quite important. When working with sensitive patient data, data security and privacy are crucial. Strict data management regulations that AI systems must adhere to are emphasised by regulatory authorities such as the GDPR. Additionally, final diagnoses are still made by human dermatologists, which means AI systems and healthcare providers must work together [11].

III. Methodology

The Deep Learning model we have used in the project development is Convolutional Neural Network (CNN). This model is an enhanced version of Neural Networks.

Other models used for classification are not exceptionally reliable because of the dependency on the user for feature identification and selection. In classification of Images, many features must be selected carefully to get a well-performing classification model.

But the advantage of CNN over other models is that they need no user intervention for the identification and selection of the features in the images for classification. The algorithm is built in such a way that the features in the images are automatically selected by the algorithm while training the model with the nodes. The complexity of the algorithm is high, and the time taken by the algorithm is more because it must learn the image features by itself.

A. Data Collection

The data we used in the training model is ISIC 2019 dataset which contains 25331 images of skin diseases categorized into 8 classes. We have collected the data set from Kaggle to acquire the data. The dataset contains a set of images with their ground truth values of which class they belong to and the meta data of the images corresponding to the patients.

The ground truth file lists the image numbers and the correct skin disease for each one. These are used to teach the CNN model what each disease looks like. The ISIC dataset has common skin diseases like melanoma, basal cell carcinoma, and actinic keratosis. It is a good dataset for training a model that can tell these diseases apart.

B. Data Preprocessing

The metadata and ground truth files are read using pandas, a tool for working with tables of data. The metadata is stored on a table, making it easy to find and use patient information. The ground truth data is changed to find the image numbers and their matching disease labels. The ground truth file has many columns, each representing a different skin disease. A value of 1 or 0 shows if the disease is in the image. This data is used to teach the model.

The images are stored in separate files, each with a unique number. According to use, the photos are converted into a format that the model can comprehend, scaled to a specific size (such as 64x64 pixels), and read using a program called PIL. This guarantees that every image is the same size, which is necessary for the model. After that, the pictures are converted into NumPy arrays, which are numerical values that may be used to train the model in TensorFlow and Keras. The numbers of any missing photos are noted for future verification. To keep the data consistent during training and testing, some missing photos are skipped.

C. Model Training

Training a Convolutional Neural Network (CNN) is a model that learns to recognize patterns and features in images through subsequent layers. A typical training of a Convolutional Neural Network is structured so that the model learns to identify patterns and features in images across multiple layers. Training begins with convolutional layers as its primary function is feature extraction. The first convolutional layer takes in the input image, say a 64x64 pixel image with three colour channels and applies multiple filters or kernels. For example, 32 filters of size 3x3.

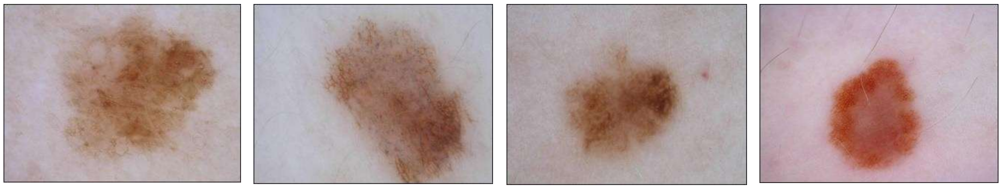


Fig 2. Sample Skin Lesions

After the first convolutional layer, a pooling operation, typically max pooling, is performed to reduce the spatial dimensions of the feature maps (width and height). This dimension reduction may reduce the most important characteristics, but it helps decrease computing complexity. The pooling layer effectively summarizes the information captured in the feature maps by focusing on the most prominent elements of the image. More convolutional layers are added as the model keeps learning. The network can identify higher-level elements like forms and particular areas of skin lesions because to the increasingly intricate patterns that each of these layers extracts from the photos.

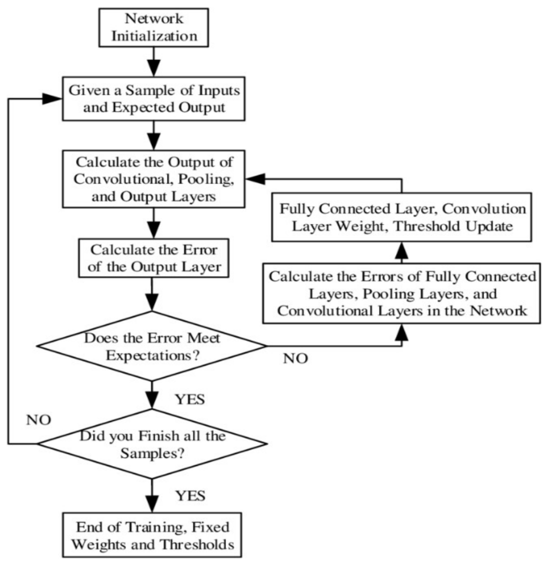


Fig 3. Sample Skin Lesions

After a few convolutional layers, batch normalisation is used to guarantee steady and effective training. By normalising the convolutional layers' output, this layer makes sure that the inputs to the following layers are scaled similarly. By improving the model's convergence, this normalisation enables it to identify the best solution faster. To prevent overfitting, dropout layers are integrated into the architecture after some convolutional and dense layers. Dropout randomly "drops" or ignores a portion of the neurons during training, which forces the model to learn more robust features that generalize better to unseen data.Once the convolutional and pooling layers have extracted the prominent features from the input image, the model transitions to the flatten layer. This layer converts the 2D feature maps into a 1D vector, which contains all the essential information gathered from the image. The flattened vector is then fed into the dense layers, which are also known as fully connected layers. These layers combine the learned features in several ways to make predictions. The first dense layer usually contains a considerable number of neurons (e.g., 256) and applies an activation function like ReLU to introduce non-linearity. This layer learns complex combinations of features that represent the underlying structure of the data. To further combat overfitting, a dropout layer may also be included after this dense layer.

The final layer of the CNN is the output layer, which is typically a dense layer with the number of neurons equal to the number of skin disease classes. This layer applies a softmax activation function to normalize the output values into a probability distribution. The softmax function ensures that the sum of the probabilities for all classes equals 1, representing a valid probability distribution. The class with the highest probability is predicted as the most likely diagnosis.

It learns through forward and back passes. After passing the image throughout all layers, the model offers a probability of each class during the forward pass. The model then uses a loss function to compare its own forecasts with the right responses. This loss indicates how bad the model's forecasts are. The model then performs a backward pass called backpropagation. The weights are adjusted during backpropagation to reduce the loss. Such optimization uses an algorithm like Adam, which changes the learning rate.

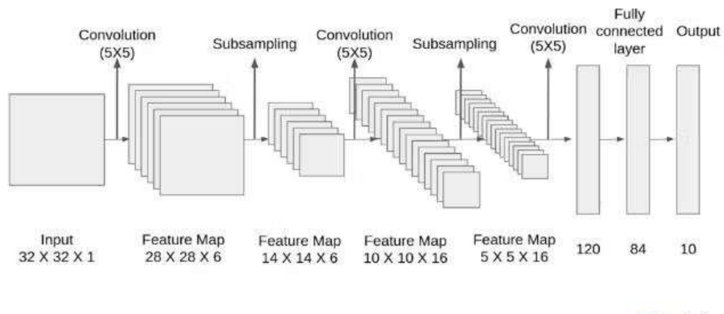


Fig 4. Sample Skin Lesions

The training happens in several epochs. In every epoch, the model is essentially going through one full cycle of its training data. The model looks at every image it is shown in these epochs and changes its weights accordingly, as told by the loss function. A validation set is also used, monitoring the performance of the model so that overfitting doesn't happen. In the process of training, the model's accuracy and loss are evaluated with this validation set so that any corrections are made if needed.

After the model has been trained, the test set with data not encountered during training is used to evaluate the performance of the model. The result will yield an objective evaluation of whether the model can generalize for novel images that were never tested on. Training a CNN is aimed at developing an effective model that could adequately classify skin conditions using the feature learned from the training data. The CNN proves useful for usage in dermatological and medical diagnostics by virtue of its capability to perform satisfactorily in real applications due to its well-defined training procedure.

D. Evaluation

The complete processes must be repeated several epochs for training on a model. This is defined as one pass through training data. During every epoch, the model computes each of the images in a training dataset and adjusts the weights based on what it has seen so far. The model can then learn to gradually improve its accuracy by fine-tuning its weights and discovering more efficient representations of the data over the course of training, which usually lasts 30 or more epochs.

During training, performance is monitored, and potential overfitting is detected through a separate validation set. Overfitting occurs when the model cannot generalize well to new, unseen data but is too specialized for the training set. An obvious sign of overfitting is when the validation accuracy starts to decline while the training accuracy continues to rise.

E. Visualization

Training results, primarily accuracy and loss, are used to understand how a model performs over time. One approach is through accuracy graphs: graphs of the training accuracy as well as the validation accuracy against numbers of epochs. Again, on the x-axis plots the number of epochs and, on the y-axis plots accuracy, sometimes as a %. You may easily see, during the training phase, how the model behaves on both datasets by using different colours or line styles for the training accuracy and validation accuracy. The graph helps you really understand the learning ability of the model and points out possible issues in terms of underfitting or overfitting.

Loss graphs are also very important for monitoring how the model is approximating during training. The x-axis has epochs, and the y-axis has the loss values, often cross-entropy loss. It's possible to monitor training loss curves and validation loss curves using the same graph but in different colours or styles. This visualization of the data allows for the tracking of how the model's error is reduced over time, which is a critical factor in determining the effectiveness of learning. The graphs produced show whether the model is converging well or is having trouble extrapolating to new data. The accuracy and loss graphs are complementary in evaluating the effectiveness of the training process and guiding potential improvements.

IV. RESULTS AND DISCUSSION

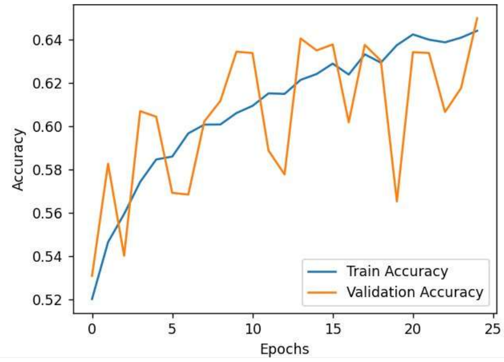


Fig 5. Accuracy

Both measures show improvement in the accuracy graph above, which depicts training and validation accuracy across 25 epochs. By the end, training accuracy has increased consistently to about 0.64. This shows that the model is using the training data to learn effectively. Though it likewise exhibits an improving trend, validation accuracy varies more sharply. These variations show that the model performs inconsistently when applied to unseen data (validation set). Overfitting, in which the model learns patterns unique to the training data that do not transfer well to fresh data, may be the cause of the validation accuracy spikes and declines. Although the model is getting better on the training set, it can have trouble generalising to new data if the validation accuracy does not steadily rise with training accuracy.

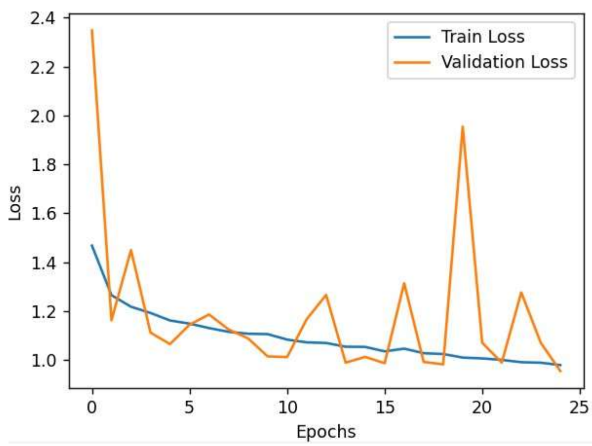


Fig 6. loss

A similar pattern can be seen in the loss graph above, which shows training and validation loss. The model is minimising errors on the training set, as evidenced by the training loss's steady drop over time. The validation loss, on the other hand, varies considerably more and exhibits multiple abrupt spikes around epochs 10, 15, and 20. The model may not be learning consistently on the validation set, based on this trend. While the validation loss trends downward, its volatility indicates that the model occasionally fails to generalize well, leading to significant errors in some epochs. This variability in validation loss, along with the accuracy graph, suggests that although the model is learning, it could benefit from techniques like regularization or early stopping to prevent overfitting and stabilize its performance on the validation set.

V. CONCLUSION AND FURURE SCOPE

The project developed is a great approach by unifying the domain of web development and Deep Learning. The product overcomes the problem of medical facilitation for the people of remote areas by diagnosing their skin remotely through an online website.

This study of skin lesions has found many distinct types of skin lesions, even unusual ones. The suggested model is believed to be able to help with many different skin problems and people. Making it easy to understand how deep learning models work is important for using them in medicine. Testing this model on many kinds of patients is important to make sure it works well in real-world healthcare. Combining this model with clinical decision support systems will make diagnosing skin diseases faster and easier, leading to better patient outcomes. This new way of classifying skin lesions can be an immense help in dermatology by finding skin diseases early and making accurate predictions about their course.

Smartphones, PDAs, and tablets are becoming important in our lives. Putting AI for diagnosing and treating skin diseases on these devices will be a big trend in the future. Most skin diseases are diagnosed using powerful computers. The computer work needed for this algorithm should be reduced while also making the algorithm better at recognizing skin diseases. This will make it easier to use on smartphones and smartwatches.

AI-powered tele-dermatology has many opportunities ahead of it. It could change the way that skin diseases are diagnosed, and remote healthcare is provided. More skin problems and even diseases unrelated to the skin can be treated by the system as AI models, particularly convolutional neural networks (CNNs), become more precise and quicker. Additionally, it might be combined with smartphone apps and wearable technology to enable patients to monitor their skin health at home. Improved natural language processing would enable the system to provide follow-up care plans and tailored treatment recommendations. If this technology is adopted globally, it could lower the number of skin cancer deaths and enable individuals in areas with inadequate healthcare to receive early diagnosis.

REFERENCES

[1] S. Islam et al., "Leveraging AI and patient metadata to develop a novel risk score for skin cancerdetection," Sci Rep, vol. 14, no. 1, Dec. 2024, doi: 10.1038/s41598-024-71244-2.

[2] K. Hauser et al., "Explainable artificial intelligence in skin cancer recognition: A systematic review," May 01, 2022, Elsevier Ltd. doi: 10.1016/j.ejca.2022.02.025.

[3] K. P. Venkatesh, K. T. Kadakia, and S. Gilbert, "Learnings from the first AI-enabled skin cancer device for primary care authorized by FDA," NPJ Digit Med, vol. 7, no. 1, Dec. 2024, doi: 10.1038/s41746-024-01161-1.

[4] B. Dulmage, K. Tegtmeyer, M. Z. Zhang, M. Colavincenzo, and S. Xu, "A Point-of-Care, Real- Time Artificial Intelligence System to Support Clinician Diagnosis of a Wide Range of Skin Diseases," Journal of Investigative Dermatology, vol. 141, no. 5, pp. 1230–1235, May 2021, doi: 10.1016/j.jid.2020.08.027.

[5] G. Brancaccio, A. Balato, J. Malvehy, S. Puig, G. Argenziano, and H. Kittler, "Artificial Intelligence in Skin Cancer Diagnosis: A Reality Check," Mar. 01, 2024, Elsevier B.V. doi: 10.1016/j.jid.2023.10.004.

[6] Z. M. Gohil and M. B. Desai, "Revolutionizing Dermatology: A Comprehensive Survey of AI- Enhanced Early Skin Cancer Diagnosis," 2024, Springer Science and Business Media B.V. doi: 10.1007/s11831-024-10121-7.

[7] L. F. Li, X. Wang, W. J. Hu, N. N. Xiong, Y. X. Du,and B. S. Li, "Deep Learning in Skin Disease Image Recognition: A Review," IEEE Access, vol. 8, pp. 208264–208280, 2020, doi: 10.1109/ACCESS.2020.3037258.

[8] S. Remya, T. Anjali, and V. Sugumaran, "A Novel Transfer Learning Framework for Multimodal Skin Lesion Analysis," IEEE Access, vol. 12, pp. 50738– 50754, 2024, doi: 10.1109/ACCESS.2024.3385340.

[9] E. Rezk, M. Haggag, M. Eltorki, and W. El- Dakhakhni, "A comprehensive review of artificial intelligence methods and applications in skin cancer diagnosis and treatment: Emerging trends and challenges," Dec. 01, 2023, Elsevier Inc. doi: 10.1016/j.health.2023.100259.

[10] C. Y. Zhu et al., "A Deep Learning Based Framework for Diagnosing Multiple Skin Diseases in a Clinical Environment," Front Med (Lausanne), vol. 8, Apr. 2021, doi: 10.3389/fmed.2021.626369.

[11] L. J. Caffery, V. Rotemberg, J. Weber, H. P. Soyer,J. Malvehy, and D. Clunie, "The Role of DICOM in Artificial Intelligence for Skin Disease," Front Med (Lausanne), vol. 7, Feb. 2021, doi: 10.3389/fmed.2020.619787.

[12] P. Tschandl et al., "Human–computer collaboration for skin cancer recognition," Nat Med, vol. 26, no. 8,pp. 1229–1234, Aug. 2020, doi: 10.1038/s41591-020-0942-0.