AI Dermatological Assistance

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Abstract- Artificial intelligence (AI) utilizes computer algorithms to carry out tasks with human-like intelligence. Convolutional neural networks, a type of deep learning AI, can classify basal cell carcinoma, seborrheic keratosis, and conventional nevi, highlighting the potential for deep learning algorithms to improve diagnostic workflow in dermatopathology of highly routine diagnoses. Additionally, convolutional neural networks can support the diagnosis of melanoma and may help predict disease outcomes. With rising rates of skin diseases and conditions globally, there is an increasing need for more accessible and affordable dermatology care. However, factors like the shortage of dermatologists, high costs of in-person appointments, and lack of access to care in rural regions present barriers to meeting this need. Recent advances in artificial intelligence (AI) and machine learning open new possibilities for developing automated systems that can conduct preliminary analysis of skin lesions and provide probable diagnoses. This research aims to develop and evaluate an AI-based tool for preliminary dermatology diagnosis that is accessible, cost-effective, and can improve care. The approach will utilize convolutional neural networks to create an image classification model trained on dermatology image datasets. The model will categorize skin lesions into different condition classes to provide a differential diagnosis. Extensive testing and validation will be done to determine the model's diagnostic accuracy across diverse dermatology cases.

INTRODUCTION

Skin diseases are a major global health burden, with over 900 million people affected by various conditions worldwide. The incidence of skin diseases has been gradually rising over the past decades due to factors like air pollution, global warming, lifestyles changes, and ageing populations. Some of the most prevalent conditions include acne, eczema, psoriasis, skin cancer, and skin infections. Timely diagnosis and treatment of these diseases is essential for improving quality of life and health outcomes. However, there is a severe shortage of dermatologists globally, with just one dermatologist available for every 60,000-100,000 people in developing countries. In the US, longer wait times for dermatology appointments can impact outcomes for potentially serious skin conditions like melanoma. The costs of in-person dermatologist visits may also be prohibitive for economically disadvantaged groups. Additionally,

those living in rural areas often lack access to specialized dermatological care.

The examination of some skin conditions by dermatologists results in significantly higher diagnostic accuracy and is associated with better clinical outcomes than non dermatologist examination. However, owing to lack of access to dermatologists, only 28% of skin cases are seen by a specialist; therefore, nonspecialists play a pivotal role in the assessment of skin lesions and initiation of clinical management and referrals. The diagnostic accuracy of nonspecialists is reportedly only 24% to 70% suggesting that currently available resources, such as dermatology textbooks, medical information portals, and online image search engines, remain insufficient to guide nonspecialists. Several algorithms incorporating artificial intelligence (AI) have been developed to help interpret both clinical and dermoscopic images for a variety of skin conditions, and the effect of AI-based support on dermoscopic images has been studied. Recent advances in artificial intelligence (AI) and machine learning, especially deep learning for medical image analysis, present new opportunities to overcome some of these barriers to accessible and affordable dermatology care. Studies have already shown that deep convolutional neural networks can classify skin lesions and diagnose disease with accuracy comparable to expert dermatologists. With further refinement, AI-based diagnostic tools have immense potential to improve access, reduce costs, and provide quicker preliminary screening in dermatology, particularly for underserved communities.

LITERATURE REVIEW

1. Xie, F., Fan, H., Li, Y., Jiang, Z., Meng, R., & Bovik, A. (2016). Melanoma classification on dermoscopy images using a neural network ensemble model. IEEE transactions on medical imaging, 36(3), 849-858.

Paper Link

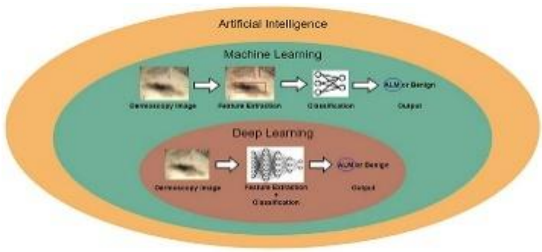
The above research paper proposed a skin lesion classification system that classified lesions into two main classes: benign and malignant. The proposed system worked in three phases. In the initial phase, a self-generating NN was used to extract lesions from images. In the second phase, features such as tumor border, texture, and colour details were extracted. The system extracted a total of 57 features, including 7 novel features related to lesion borders descriptions. Principal component analysis (PCA) was used to reduce the dimensionality of the features, which led to the selection of the optimal set of features. Finally, in the last phase, lesions were classified using a NN ensemble model. Ensemble NN improves classification performance by combining backpropagation (BP) NN and fuzzy neural networks. Furthermore, the proposed system classification results were compared with other classifiers, such as SVM, KNN, random forest, Adaboost, etc. With a 91.11% accuracy, the proposed model achieved at least 7.5% higher performance in terms of sensitivity than the other classifiers.

2. Himanshu Chaudhary, Ruchita Gautam, Praveen Kumar, Abhishek Sharma 2023 International Conference on Sustainable Emerging Innovations in Engineering and Technology (ICSEIET), 458-463, 2023.

The text outlines a proposal to use deep learning, particularly CNNs, for early skin cancer detection. It emphasizes the urgency of timely diagnosis and describes the method, including various CNN architectures and a web application for image analysis. The goal is to enhance diagnostic efficiency and accessibility, ultimately improving patient outcomes.

AI IN DERMATOLOGY

A dermatologist is a doctor that treats conditions that involve the skin, hair, and nails. AI has the power to restructure dermatology by improving accuracy, efficiency, and patient outcomes. In dermatology, the most useful aspect of AI is to utilize imaging to analyze skin cancer, ulcers, and psoriasis; image analysis is an AI-powered tool that can be utilized to recognize and distinguish lesions. The process includes analysis of each pixel in the image and validation and cross-checking with a certified dermatologist. In general, Deep Learning (CNN) is utilized to analyze the data through a neural network that mimics the human brain. In terms of Mohs micrographic surgery, AI studies tumor size and patient age, so the dermatologist can better determine which patients should be prioritized. For ulcer treatment, AI can determine ulcer impacts by measuring wound boundaries. Potential early detection of certain skin diseases can aid in improving patient outcomes and health. Apart from image analysis, AI can complement a physician in choosing the best intervention depending on patient data (age, sex, ethnicity), creating less room for medical error and again contributing to improved patient outcomes. Lastly, AI can help improve the efficiency of a Dermatology practice by helping automate appointments, case files, and referral letters. A major AI component in dermatology is teledermatology, in which skin disorders can be analyzed through imaging. Companies such as DermDetect have played a major role in bringing dermatological AI to use by a wide range of customers that require skincare but do not have the means to meet a dermatologist in person. Besides the medical aspects, AI is also utilized to effectively manage patients in the hospital. Programs such as Hello Rache have been actively used to analyze a patient-physician interaction during an appointment and automatically convert it into writing. These types of technologies will ensure healthcare professionals do not spend their time on repetitive tasks, which can increase their workload. Fortunately, these AI technologies are available to purchase through the internet. It has become more popular in private clinics because it allows physicians to reduce the workload and increase the number of patients seen daily. The AI applications open as of now are already changing the status quo of dermatological care around the world. However, necessary innovation is still required for progression into phase three of AI’s usage in the clinical setting.



AI could help address the shortage of dermatologists, the uneven distribution of medical resources, and the need for more diverse and accessible treatment options. With the increasing incidence of skin disease and shortage of dermatologists, AI can create a metamorphic change in turnaround time and accessibility of dermatological care. AI-based care also allows for fewer slip-ups in a medical setting providing personalized care for patients as it can evaluate vast databases and cross reference those to tailor care for patients avoiding any negative reactions to care. Furthermore, AI could also be used to create more effective care by focusing research efforts on fruitful approaches by using AI to simulate testing, which can both reduce the cost burden of research and add efficiency. AI integration into interactive educational access points can improve public health by improvement of knowledge. For example, a mobile application called "Sunface" can assess a user's skin according to facial features and skin type and provide a tailored recommendation for sunscreen and skin care products. Sunface not only helps users choose the right products but also reminds users daily to apply sunscreen to help preventthe incidence of sun damage-associated skin disease. With the integration of AI-aided systems into routine dermatology, faster and more accurate diagnoses could become the norm.

METHODOLOGY

1. DATA COLLECTION

Training of neural networks for automated diagnosis of pigmented skin lesions is hampered by the small size and lack of diversity of available datasets of dermatoscopic images. We tackle this problem by collecting the HAM10000 ("Human Against Machine with 10000 training images") dataset which are available on the online platform. The final dataset consists of 10015 dermatoscopic images which are released as a training set for academic machine learning purposes benchmark dataset can be used for machine learning and for comparisons with human experts.

1. The dataset consists of 10015 dermoscopic images with 7 target disease.

Such as:-

1. Actinic Keratoses [akiec]: Types of squamous cell carcinoma that are noninvasive and can be treated locally without surgery (327 images are available in the data set).

2. Basal Cell Carcinoma [bcc]: A type of epithelial skin cancer that seldom spreads but, if left untreated, can be fatal. (514 images are available in the data set).

3. Benign Keratosis-like Lesions [bkl]: Seborrheic keratoses, lichen-planus like keratoses, and solar lentigo, correlate to a seborrheic keratosis or a sun lentigo with regression and inflammation, are all examples of "benign keratosis" (1099 images are available in the data set).

4. Dermatofibroma [df]: Skin lesions that are either benign growth or an inflammatory response to minor trauma (115 images are available in the data set).

5. Melanoma [mel]: Melanoma is a cancerous tumour that develops from melanocytes and can take many different forms. If caught early enough, it can be treated with a basic surgical procedure (1113 images are available in the data set).

6. Melanocytic Nevi [nv]: Skin lesions are benign neoplasms of melanocytes and appear in a variety of shapes and sizes. From a dermatoscopic standpoint, the variants may differ dramatically (6705 images are available in the data set).

7. Vascular Lesions [vasc]: Cherry angiomas, angiokeratomas, and pyogenic granulomas are examples of benign or malignant angiomas. (142 images are available in the data set).

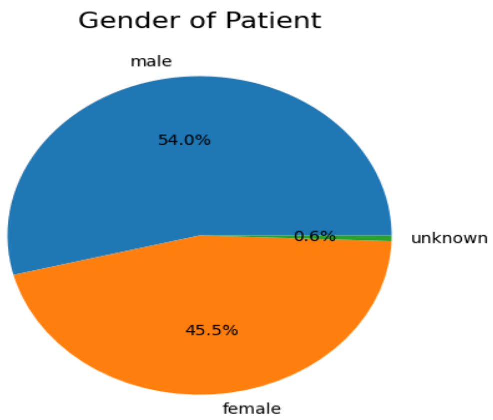
The dataset also consists of a ham 10k Metadata file that provides information about a particular images like how the disease is confirmed using either histopathology or follow-up localization of disease Age of patients, Gender, Diagnosis method, Localization of disease etc. These descriptive parameters would be used for trained model.

Dataset	*License*	*Total images*	*Pathologic verification (%)*	*akiec*	*bcc*	*bkl*	*df*	*mel*	*nv*	*vasc*
PH2	Research&Education[a]	200	20.5%	-	-	-	-	40	160	-
Atlas	No license	1024	unknown	5	42	70	20	275	582	30
ISIC 2017[b]	CC-0	13786	26.3%	2	33	575	7	1019	11861	15
Rosendahl	CC BY-NC 4.0	2259	100%	295	296	490	30	342	803	3
ViDIR Legacy	CC BY-NC 4.0	439	100%	0	5	10	4	67	350	3
ViDIR Current	CC BY-NC 4.0	3363	77.1%	32	211	475	51	680	1832	82
ViDIR MoleMax	CC BY-NC 4.0	3954	1.2%	0	2	124	30	24	3720	54
HAM10000	CC BY-NC 4.0	**10015**	53.3%	327	514	1099	115	1113	6705	142

2. Exploratory Data Analysis

From our dataset we observed these meaningful insights:

Gender wise differentiability:



• It seems majority of the male being affected from skin cancer symptoms 54%.

• Though we can say there is not too much difference when considering being affected gender wise.

Cell type affect on.

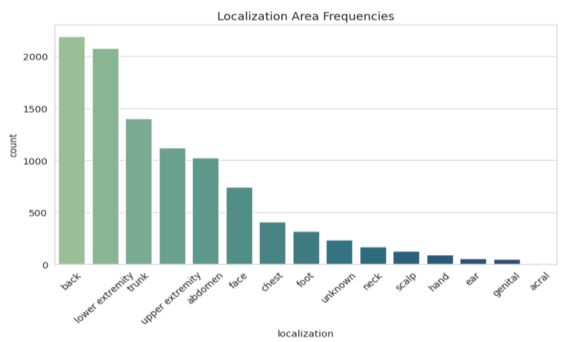
• There are vast number of cases of Melanocytic nevi as compared to others.

• Melanoma and Benign keratosis-like lesions are quite less wide spread as compared to Melanocytic nevi.

• Melonoma which is more critical is less wide spread.

Other cell type viruses subsequently affected less in numbers.

Localization area:-

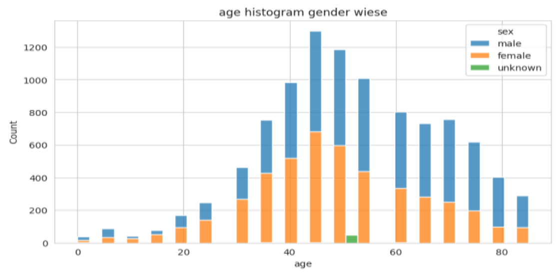


• We can see that the most affected areas are back and lower extremity.

• It seems most of the area affected is related to particularly back, lower extremity or trunk etc.

• The significance we take out of it as the areas where the part gets sweaty easily.

Age:



• It seems most of the affected people are around mid 40s

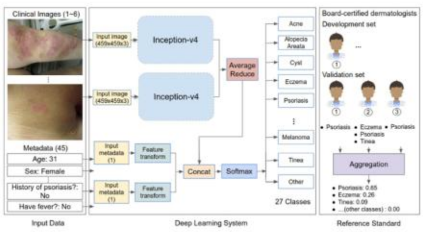
3. Model Training :

For training our model we are using a CNN (Convolutional Neural Network) model. A CNN (Convolutional Neural Network) is a type of artificial neural network designed for processing structured grid data, such as images. It consists of multiple layers, including convolutional layers, pooling layers, and fully connected layers. CNNs use convolution operations to detect patterns and features in input data, and they employ techniques like pooling to reduce spatial dimensions and increase computational efficiency. Convolutional NNs (CNNs) are a special subclass of ANNs that contain one or more layers called convolutional units (pooling units). CNNs take in two-dimensional or three dimensional inputs which are passed through multiple hidden layers. An image can be broken down into motifs, or a collection of pixels that form a basic unit of analysis. The first few layers of the CNN compare each part of an input image against some small sub-image. CNN model is consist of some pretrained model which is called as a pretrained-CNN. These pretrained CNNs are often trained on databases that include millions of images, so they are able to distinguish images with much higher accuracy than a CNN that is only trained on databases of only a few hundred or few thousand images. The last fully connected layer of a pretrained CNN is modified and trained with images for the more specific classification task. Examples of common pretrained CNNs are A Googles Inception V3 and VGG-16.

I) Inception V3 : Inception is a CNN Architecture Model. The network trained on more than a million images from the ImageNet database. The Pre trained network can classify images into 1000 object categories, such as keyboard, computer, pen, skin diseases and many things. Inception v3 is a 48-layer convolutional neural network (CNN) that helps with image analysis and object detection. It's the third version of Google's Inception CNN, which was first introduced during the ImageNet Recognition Challenge. Inception v3 is an image recognition model that has an accuracy of over 78.1% on the ImageNet dataset. Introduced in 2015.

II) MobileNet-V2: A lightweight convolutional neural network (CNN) architecture, MobileNetV2, is specifically designed for mobile and embedded vision applications. Google researchers developed it as an enhancement over the original MobileNet model. Another remarkable aspect of this model is its ability to strike a good balance between model size and accuracy, rendering it ideal for resource-constrained devices.

The use of MobileNetV2 for image classification offers several advantages. Firstly, its lightweight architecture allows for efficient deployment on mobile and embedded devices with limited computational resources. Secondly, MobileNetV2 achieves competitive accuracy compared to larger and more computationally expensive models. Lastly, the model's small size enables faster inference times, making it suitable for real-time applications.



4. Model Evaluation :

Here we train our dataset with two pre-trained architecture of CNN model with 30 epochs which consume lot of time and computation power. So the models are

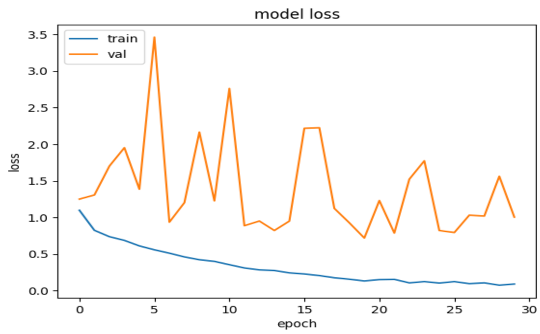
- MobileNet-V2

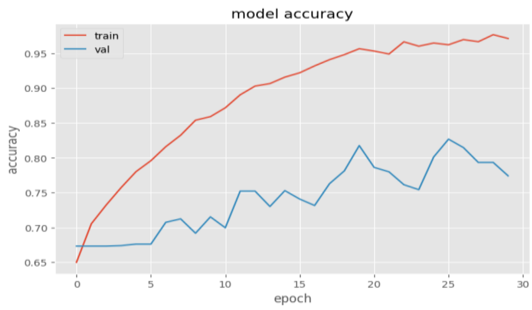
- Inception V3

With the help of MobileNet-V2 pre-trained model we got almost 77% accuracy and below graph shows that as epochs size increases the models accuracy also increases and at the same time model's loss decreases.

We save this pre-trained model in .H5

```
model.save("model12345.h5")
```

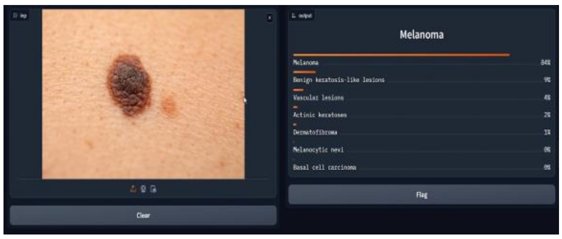


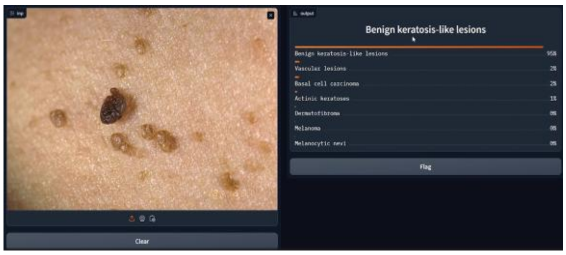


5. Results :

Gradio is an open-source Python package that allows you to quickly build a demo or web application for your machine learning model, API. Then we can share a link to our demo or web application in just a few minutes using Gradio.

So using gradio we created an user friendly interface where user can upload the images of various kinds of skin diseases and it will give an output showing which disease it is.





CONCLUSION

The integration of artificial intelligence (AI) into dermatology assistance holds significant promise for revolutionizing the field by improving diagnostic accuracy, efficiency, and accessibility. Convolutional Neural Networks (CNNs) and other

AI models have demonstrated impressive capabilities in analyzing dermatological images, aiding in the identification and classification of various skin conditions. However, despite the advancements made, several challenges and limitations remain. These include issues related to data quality and diversity, interpretability of AI-generated diagnoses, ethical and legal considerations, integration with clinical workflows, and the need for ongoing model updates and validation. Addressing these challenges will require collaborative efforts from researchers, clinicians, ethicists, policymakers, and technology developers. Moving forward, it is essential to prioritize the development of AI systems that are not only accurate and reliable but also transparent, interpretable, and equitable. Additionally, efforts should be made to ensure that AI-driven dermatology assistance complements rather than replaces human expertise, fostering a synergistic relationship between AI and healthcare professionals for improved patient outcomes. With continued research, innovation, and responsible implementation, AI has the potential to enhance dermatological practice, empower clinicians, and ultimately improve the quality of care for patients worldwide.

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