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Systematic investigation on Multi-Class skin cancer categorization using machine learning approach

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A B S T R A C T

In recent years, AI emerging as a technology capable of solving problems related to agriculture, health care, business, and soon. To reduce the risk to human life we can adopt machine learning algorithms in the health care domain and can predict the deadliest skin diseases such as malignant melanoma in early stages. The aim of the paper is to provide insights about different categories of skin lesions and methodologies implemented to classify and predict skin cancers, and the role of dermatologists while developing the models, finally provides an overall summary of existing work. The work here presents a systematic comparative study on various algorithms with their advantages and limitations leading to effective conclusions on further directions of research in this area.

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1. Introduction

Recent survey reports state that globally around 5.4 million people are affected by the deadliest skin disease melanoma skin cancer [6], in the US over 3.3 million people suffered from melanoma skin cancer [5]. If the spread of the disease not controlled in the early stage can result in the death of the human [1]. Even it is reported that the U.S spending around $8.1 billion for the treatment of skin cancer [7]. Over worldwide and in the U.S skin cancer is the most well-known disease among other diseases, it need to identify at an early stage to cure the disease and reduce the risk, otherwise it can lead to death of the person.

Skin tumours can be of category melanoma [9] and non-melanoma. Melanomas a risky type of skin malignancy, they can create from existing moles; however, they all the more frequently appear as a novel check on the skin. Melanomas can show up on any aspect of the skin however they are generally basic in men on the body, and in ladies on the legs [22,29]. Dangerous melanoma may attack further layers of the skin and can spread to different regions of the body, sample image unveil in Fig. 1, Malignant Melanoma can be treated and removed if they caught early with a method so-called surgery- wide excision, wherein the surgeon removes the entire tumour region along with some portion of the healthy skin around it [3] publicized in Fig. 2.

Multi-class skin diseases categories [29]: • psoriasis, portrayed skin sore with the shading red or pink and of different estimations, protected secured with white scales and joined by shivering and chipping; usually affected human body portions of the skin are the scalp, elbow and of the knee; • seborrheic dermatitis, the commonplace provocative skin condition causes flaky, appear on smooth zones, for instance, the scalp, eyebrows, and surroundings of nose, or around the ear; the infected region shaded in red and irritated; • lichen planus, typical bothersome, non-infectious dermatitis comprised of sparkling, a little bit inflamed purple and reddish shades appears around the lower legs and back; • a skin rash of red injuries known as pityriasis rosea, that spread over the whole body and it causes tingling; • constant dermatitis, shows by rosiness skin, irritation, tingling, and some portion of wound; these wound are situated around the neck, wrist, lower arm, thigh, lower leg etc; • pityriasis rubra pilaris, described by rosy orange scales, serious chipping, awkward tingling, thick and leathery of the skin on the region of the scalp, hands, and feet.

2. Literature survey

Skin infection is an abnormal stipulation of the skin. Henceforth the right determination of skin cancer is significant; the largest organ of the human-skin assumes a significant part in shielding

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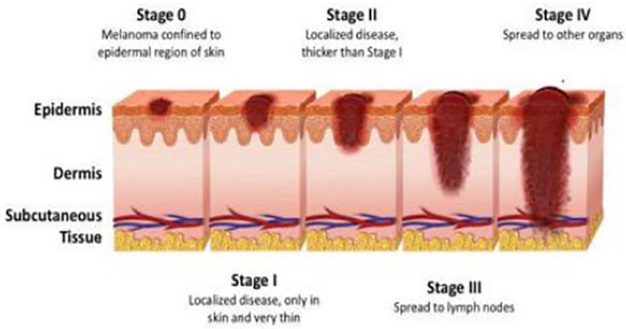


Fig. 1. Melanoma stages [12].

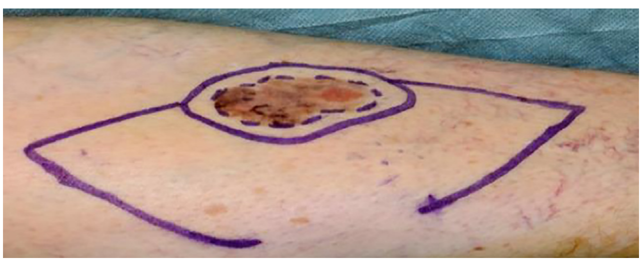


Fig. 2. Surgery –Wide Excision [13].

the body from unsafe bacterial, contagious, and parasitic contaminations. The factors such as hereditary qualities, occupation, nourishment, propensities, and so on can cause skin illnesses and influencing skin disorder patterns. Moreover, overcrowding, poor hygiene, and geological components like season and atmosphere additionally effect and cause the dispersal of skin infections. The patterns of skin infections differ nation to nation and depend on ethnic groups. To detect the high-risk diseases [30] in the early-stage and image characterization, and Automated detection [35] system needs to develop for the urban, semi-urban, and remote areas where dermatologist access is limited [20,21].

A user-friendly application and image processing technique model need to be created, can available even in far-off regions and it is totally non-intrusive to the patient's. Where infected person gives the contaminated portion of the skin image as an input to the mobile or web-based application. The model ought to show the recognized disease, its severity or impact, and concerns. To faster diagnosis some diseases with various, befuddling side effects, and to improve decision –making a deep learning model [22] can be useful and strongly impact physicians to make appropriate diagnosis well in time. Stephanie Chan et al., [7] implemented a pre-trained Convolutional Neural Network (CNN) model –ResNet 152 to identify basal-cell-carcinoma, squamous-cell-carcinoma, and malignant melanoma skin lesions, model trained using a training dataset consists of 19,398 instances of clinical and dermatopathology images, later model examined the patients data related to asian and caucasian instances to diagnosis twelve diseases but model biased and generated accuracy is varied based on patient ethnicity. Tschandl, P., et al., [18] looked at the analytic exactness of AI calculations with the human reader to recognize threatening and favourable skin sores, for example, intraepithelial carcinoma, basal cell carcinoma; considerate keratinocyte injuries and s. Where 11,210 dermatoscopic instances were utilized, information gathered from ViDIR (Vienna-Dermatologic-Imaging-Research Group), the proposed model AI calculations accomplished a mean of 7.94 more right determinations than the normal human readers and a mean of 6.65 more right conclusions than expert readers.

Advances in the technology can help to store adequate clinical data and make available to a clinical specialist; the clinical data may include clinical symptoms to different kinds of biochemical information and yields of imaging gadgets. Each variety of information gives data that must be assessed and allotted to a specific pathology during the indicative cycle. To smooth out the diagnosis process in everyday schedule and stay away from misdiagnosis, AI techniques can be adopted. These ingenious erudition techniques can deal with diverse kinds of clinical information and facilitate them into sorted yields [23]. Rezvantalab, A. et al., [10] used DenseNet-201; ResNet-152 techniques for predicting skin cancer, around 10,135 dermoscopy images of HAM100000 and PH2 data set are used to train the model. The proposed model outperformed than dermatologists and the accuracy achieved by these algorithms are satisfactory for specific dataset HAM100000 and PH2, whereas for diverse data set accuracy are still not satisfactory. In digital biomedical images, the skin cancer region can be outlined by the techniques known as partial-differential equations (PDE) [26]. Where pre-processing algorithms such as histogram equalization applied for enhancement [34] of biomedical images [32], later mathematical morphology via PDEs, and a straight line segment of erosion-dilation adopted to remove hair, to segment the skin lesions geodesic edge tracing or the geodesic active -contours model are implemented. Maron, R. C., et al., [2] projected a model convolution neural network to categorize the skin cancer into Melanoma, Nevi, and Basal cell carcinoma, dermoscopic instances of 11,444 are used to train the model and the model was able to achieve better specificity of 96.6% for Nevi skin disease, whereas model achieved the lowest specificity 94.2% for Melanoma skin disease.

Hekler, Achim, et al., [4] proposed the fusion model shows superiority over a separated approach. The proposed method used 11,444 dermoscopic images of the HAM10000 Dataset; the model achieved accuracy 42.94 for Physician, 81.59 for the pre-trained CNN model, and 82.59 for the combined Fusion method. Therefore proposed model outperformed with the combination of the human and pre-trained models. Zhang, N., et al., [14] developed a model that detected skin cancers such as FCC and melanoma. The paper focused to generate better specificity and accuracy by adopting the Whale algorithm to optimize a CNN model, The proposed model trained using 22,000 instances of Dermquest and Dermis dataset and the result produced by the optimized CNN model compared with other models such as the ordinary CNN model [36], AlexNet, and ResNet, the proposed model generated highest value of specificity 98%, the accuracy of 94% and sensitivity of 97%, however for non-melanoma case results are not satisfactory.

Support Vector Machine [24] classification model adapted [25] to classify three categories of skin diseases such as dermatitis, herpes, and psoriasis based on text features and image colour. Fujisawa, Y., et al., [15] implemented the GoogleNet CNN model to predict the deadliest diseases [28], the model outperformed than the trained dermatologist with 96.3% of sensitivity, the automated model trained using 4800 clinical images, and the model works efficiently for homogenous images, whereas sensitivity and specificity dropped for Caucasian patients. To compress image [52] effectively without loss of precision value [53] proposed a scalable and robust model, such as fast search cuckoo [27] technique for fractal image compression, whereas range block size used to improve fractal image compression [33]. Zakhem, G. A., et al., [16] demonstrated that the model can be outperformed with the involvement of dermatologists while training the model. The paper show 1279 dermoscopy images are used to train the ResNet model, able to classify instances as melanoma or benign lesion and model achieved an accuracy of 89.2% without the involvement dermatologist whereas the model achieved an improvement of 94.3% accuracy with the association of a dermatologist. Pacheco,

A. G., et al., [1] designed a model to envisage most common skin lesions like basal cellcarcinoma, seborrheic keratosis, actinic keratosis, melanoma, squamous cell carcinoma, Nevus and Bowen's diseases, and the multilayer [31] model ResNet-50 shows improvement in result by adding additional clinical features such as patient age, bleedings, itch, etc., along with skin lesion images. The accuracy achieved for clinical images is 67.1% whereas the model achieved 78.8% of accuracies by adding clinical data along with the images.

Dr. Alexander Ngoo et al. [19], provided information about the availability of the various smartphone apps to detect malignant melanoma. These mobile applications can help clients in essential or auxiliary avoidance of skin disease. There are numerous kinds of them; the author grouped them into four distinct types such as

a. Education Apps – gives valuable data to the end-user regarding melanoma or skin malignancy deterrence (ultraviolet rays, burns caused due to exposure to sunlight).
b. Risk assessment Apps- survey singular patient risk factors for skin malignancy to make them mindful of their threat.
c. Examination of spots or moles either by means of a trained model or sending of pictures to a skin doctor or medic.
d. Mole Map - recognizing or observing injuries after some point in time through or lacking the supervision of a body map.

The key observation from the paper [19], there has been a decisive decrease in the extent of apps that were engaged with com-

Table 1
Demonstrates a comparative report of different algorithms.

SNo.	Author /Year of publishing	Objective	Algorithms used	Result / Accuracy	Limitations
1	Stephanie Chan et al. [7], 2020	Current applications , Opportunities, and Limitations- to classify skin cancer	• ResNet• Hallym dataset 19,398 instances are used	For Basal Cell Carcinoma (BCC)• 96% for asian dataset• 90% for the instances of caucasianFor Melanoma –• 96% for the instance of asian• 88% for caucasian dataset	Model performance depends on patient ethnicity
2	Ni Zhang et al. [14], 2020	Skin cancer diagnosis based on Optimized Convolutional Neural Network	• Whale algorithm applied to optimize the CNN model• Around 22,000 images of Dermquest and DermIS dataset were used	Achieved :• Specificity – 98%• Accuracy- 94%• Sensitivity-97%• PPV-90%	Results are unsatisfactory for non – Melanoma cases
3	Andre G.C, Pacheco et al. [1], 2020	Computerized-skin lesion system performance can be improved by implanting clinical data along with clinical images	• ResNet• Clinical images• Clinical data are included	Achieved :• 67.1% for clinical images• 78.8% for clinical data and images	• Missing values are not handled in clinical data• Biopsy images are not included
4	Zakhem et al. [16], 2019	Outperformed AI applications can be designed by involving dermatologists	• ResNet• 1279 dermoscopic instances are used.	• Achieved 89.2% for ResNet without dermatologist• 94.3% for ResNet- with dermatologist.	• Clinical information to be included• No standard evaluation criteria exist to measure classification efficacy
5	AchimHekler et al. [4], 2019	Skin malignancy categorization by the amalgamation of individual and intelligent machine	• ResNet• HAM10000 dataset, ISIC archive- 11,444 dermatoscopic instances are used	Mean accuracy of• Physician –42.94• CNN model – 81.59• Fusion model – 82.59	Model outperformed for the trained dataset, but performance degraded for other datasets.
6	E. Goceri et al. [26], 2019	Categorization of Skin disease using Deep Neural Network techniques and different activation functions ReLU and SeLU	• ResNet• Dermnet dataset provides an instance of 23 categories of skin diseases	Achieved 97.1%	Able to identify few skin disease like• Acne , Rosacea, Hemangioma,• Psoriasis, Seborrheic Dermatitis
7	K. Melbin et al. [35], 2019	Optimized Dragonfly based DNN to detect skin diseases	Dragonfly optimized DNN model is assessed using existing techniques such as Support Vector Machine, ANN, and to display the efficiency of the system diverse evaluation criteria's are accuracy,sensitivity, and specificity are considered	Achieved• Sensitivity – 84%• Specificity- 99.5%• Accuracy – 98.5%	Result generated for Melanoma is inadequate
8	Roman C. Maron et al. [2], 2019	Multiclass skin tumor image categorization through CNN models	• CNN model used to Categorized the skin cancer into Melanoma, nevi, basal cell carcinoma• 11,444 dermoscopic images HAM10000 dataset, ISIC archive was used .	• 89.2% of specificity and 56.5% of sensitivity attained by the dermatologists• Whereas the CNN model achieved 98.8%. of sensitivity,and specificity	• Model biased and failed to classify skin lesion properly• For melanoma images CNN model diagnosed it as nevi whereas dermatologists diagnosed it as melanoma• model achieved the lowest specificity 94.2% for melanoma class
9	Fujisawa Yasuhiro et al. [15], 2019	Automated system that identifies skin tumor	• GoogleNet CNN model• 4800 clinical images	Achieved• Sensitivity –96.3%• Specificity –59.5%	• Model behaviour depends on skin colour tone, and Model biased, sensitivity and specificity dropped for Caucasian patients• No standard evaluation criteria exist to measure classification efficacy
10	Rezvantalab et al. [10], 2018	Skin disease identification at Dermatologist level through Different Deep Neural Networks Algorithms	• DenseNet, ResNet model results compared with Dermatologist• 10,135 dermoscopy images of HAM10000: 10015, PH2: 120 data sets are used	For Melanoma and BCC – achieved94.40% for ResNet, 99.30% for DenseNet whereas Dermatologist achieved – 82.26% and 88.82% accuracy	• Model biased for the diverse dataset• Model behaviour depends on skin tone colour

Fig. 3. (a) Skin cancer looks differently in skin tone colour; (b) An unusual type of moles pointed in a circle is a Melanoma [7,8].

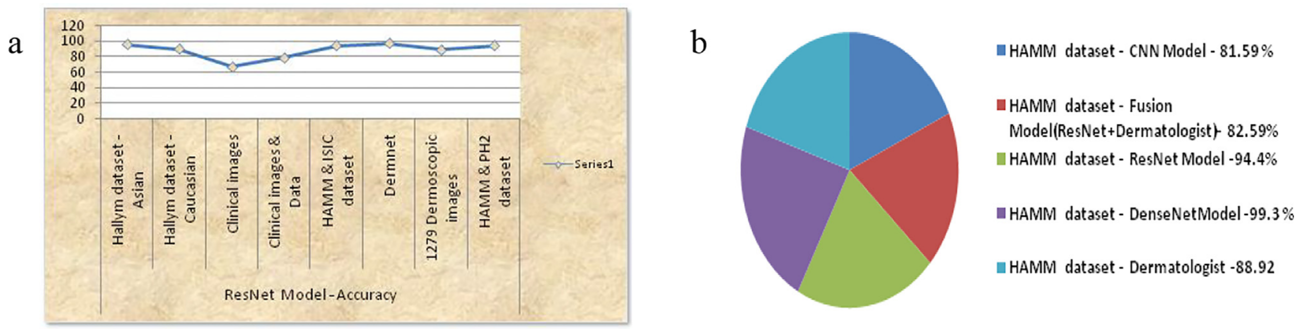
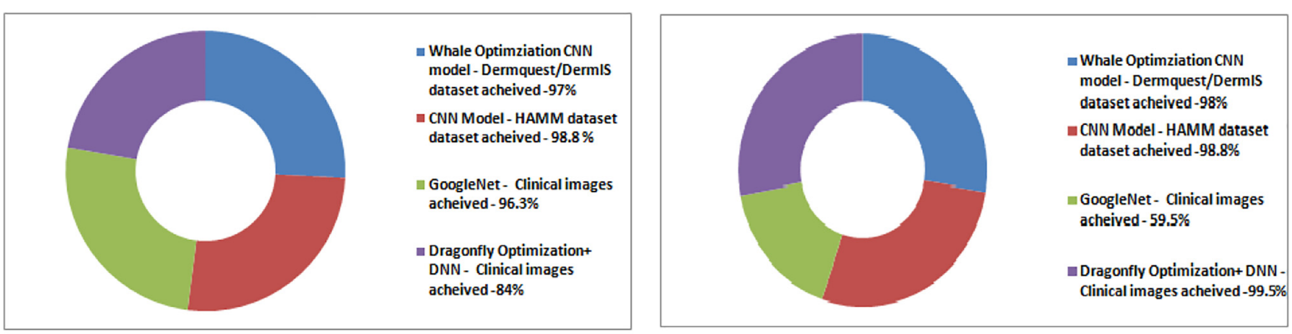


Fig. 4. (a) Displays performance of ResNet model on diverse datasets; (b) DenseNet model outperformed for the HAMM10000 dataset.



a b

Fig. 5. (a) Displays sensitivity; (b) Displays specificity achieved by models.

puterized picture investigation or diagnosis. It remains worried that most of the apps studied keep on lack of peer-reviewed evidence to back their adequacy. This paper gives a survey of Machine learning algorithms used in various articles; second, we analyze the dataset, accuracy, and result. In the end, we investigate constraints and probable defy for the potential improvement of Machine Learning algorithms. This paper provides a leading path for researchers and dermatologists to understand the basics algorithms in ML and broad extent of uses. Table 1 presents a comparative report of the diverse algorithms used to recognize and classify diverse skin cancer.

2.1. Focused challenges

One of the significant areas where Artificial intelligence providing a service is health care [49–51], and shows the most trustful is in diagnostics. Early recognition of the disease like lung cancer, heart [40–44], malaria [17], thyroid [11], the tumour [12] can keep away from the risk and shave down the time it takes to analyze and diagnose the serious illnesses. However to design a robust, automated, and reliable diagnostic tool for medical application [45–48], need to consider a few challenges such as

1. Algorithm biases**:** It was noticed that AI model prepared on Asian pictures as appeared in Fig. 3a, performed more regrettable on patients of the Caucasian [7], i.e., the algorithms designed for skin tone fair colour misdiagnoses for the dark coloured skin tone and the cutaneous infections shown diversely for the dark skin [8]. So a model intended to develop, that functions admirably for the differing dataset and ought to be without ethnic and high accurate.
2. Algorithm misdiagnoses: If an algorithm misdiagnoses a harmful sore its effect will be serious, if a prepared model incapable to disclose to a sufferer why it examine a tumour as threatening or mild, can be conceivably risky and dangerous for the patient, Fig. 3b, demonstrates a risky melanoma that looks almost similar to a normal mole.
3. Achieve robust skin [40] disease diagnosis: dermatologist requires a significant level of skill and precision to diagnose deadly skin diseases, so a strong automated skin disease diagnosis model is required [37–39] that provide better accuracy, and reliable prediction. Numerous kinds of examination never really recognized skin infections like skin malignancy. But the precise acknowledgment of the sickness is incredibly testing because of the accompanying reasons: visual matching skin

portion among non-disease and disease, images with low clarity, and so forth. The noise or unwanted things in a skin image can be removed by applying filters, and converting the image into grey can help us to analyze and detect the skin disease accurately
4. Develop a user-friendly deep neural network-based application [52,53] for assisting dermatologists remotely and helps in taking proper decision making is challenging, i.e. early prediction of skin cancer can avoid the death of a person, even spread to other body parts can be controlled.

3. Data set

The available dataset are HAM10000 (10015 images), PH2 (120 images), ISIC archive, ViDIR - Vienna Dermatologic Imaging Research Group, Dermnet, Dermatology Data Set (366 instances), Dermquest, and Dermis (22000 –dermatoscopic images). Fig. 4 (a), shows ResNet outperformed 97.1% accuracy for the Dermnet dataset, whereas Fig. 4(b) illustrate the DenseNet model achieved an accuracy of 99.3% for the HAMM10000 dataset and DenseNet model outperformed compared to the other CNN, Fusion, ResNet model, and dermatologist, and Fig. 5 shows sensitivity and specificity of diverse model.

4. Conclusion

Advancements in machine learning techniques help to design a model for the medical image classification and accomplished promising outcomes in the latest years. Even although an automated diagnostic assist gadget exists to diagnose pores and skin most cancers, still we require models that can diagnosis multiclass skin cancer. Especially, ResNETs have been utilized since they can dispense with the disappearing gradient issue is exceptionally neural networks. Nonetheless, ResNet models with various batch sizes, instances count of training and testing stages, and diverse activation function can cause various outcomes. From Table 1 we can conclude that ResNet achieved better accuracy 97.1% for the dataset Dermnet, whereas the DenseNet neural network model outperformed among all other models for the HAMM10000 dataset with an accuracy of 99.3%, and Roman C. Maron et al. proposed CNN model achieved a maximum sensitivity of 98.8% whereas K. Melbin et al. proposed Dragonfly optimized Deep Neural model achieved the highest specificity of 99.5%, and Rezvantalab et al. proposed model biased behaving differently to the diverse dataset. Andre G.C, Pacheco et al proposed model achieved a low accuracy of 67.1% for the clinical images. However to get a significant assessment of the outcomes, we need to design a model that works well to the diverse dataset and unbiased, that can be achieved by creating open access, standardized, larger skin tumour images data set (conventional/ dermoscopy), that includes rare tumours and all ethnicities.

CRediT authorship contribution statement

S. Naresh Kumar: Conceptualization, Methodology, Software, Data curation, Visualization, Investigation, Writing - original draft. **B. Mohammed Ismail:** Supervision, Software, Validation, Writing - review & editing.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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