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MULTICLASS MEMBRANE GASH UNCOVERING AND TAXONOMY USING AMALGAM FEATURES SELECTION BASED ON DEEP CNN

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ABSTRACT

One of the primary steps toward clinical therapy may be doing an appropriate sickness analysis. In summary, the area of dermatology is arguably one of the most unpredictable and demanding. Dermatologists always need more patients in order to get the correct conclusion because, all things considered, skin injuries are a severe condition that can affect individuals. For instance, it is essential to have astute frameworks for analysing skin malignant growth early on and, more specifically, to identify and prioritize skin injuries. Subtypes of skin sores that are generally referred to as multiclass skin injuries include Basal Cell Carcinoma (BCC), Melanocytic Nevus (NV), Melanoma (MEL), Actinic Keratosis (AK), Harmless Keratosis Injury (BKL), Squamous Cell Carcinoma (SCC), Dermatofibroma (DF), and Vascular Sore (VASC). The numerous skin injuries and their high likenesses make the multi-class groups still a difficult task. To physically distinguish various skin lesions from dermoscopy photographs, a significant amount of investment and expenditure is required. Therefore, it is crucial to develop computerized diagnostics techniques that can more accurately classify various types of skin lesions. Subsequently this review presents Multiclass skin injury recognition and order using mixture highlight determination in light of Profound Convolutional Brain Organization (DCNN). The presentation of the design is evaluated based on its awareness, accuracy, and explicitness.

Keywords: *Skin lesion, Hybrid structures selection, DCNN,*, *Dermatology*

1. INTRODUCTION

Dermatology focuses on a wide range of skin diseases and disorders, of which skin malignant development is just one. The majority of the findings in this field of study are based on the skin's outward appearance. As a result, to investigate skin infections, many imaging techniques such as reflectance confocal microscopy, dermoscopy, and ultrasound are used [1]. Skin disease is the most often known type of cancerous development on the earth. Numerous structures can develop skin cancers, such as melanoma, intraepithelial carcinoma, squamous cell carcinoma, and basal cell carcinoma. The three tissues that make up human skin are the epidermis, the dermis, hypodermis. Under any conditions, melanocytes in the epidermis can produce melanin at a very peculiar pace [2].

Recently, skin images from several imaging processes have been captured. Dermoscopy is a painless imaging technique that provides a picture of the skin's surface by using a soaking liquid and light amplification. However, due to expert knowledge, the common understanding of where melanoma is located in skin lesions may be inaccurate, ill-defined, or difficult to replicate.

Skin sores are areas of the skin that appear different from the surrounding skin. They can be caused by a number of problems and frequently appear as knocks or fixes. The American Society for Dermatologic Medical Procedure defines a skin injury as an oddity, bump, ulcer, sore, or coloured area of the skin. Notwithstanding the validity of the dermoscopy skin sickness conclusion, it is extremely challenging for skilled dermatologists to accurately identify benign skin sores and dangerous melanoma for a significant percentage of dermoscopy images due to the variety of skin surfaces and wounds.

Mechanical advancements to alter the clinical medical care framework have given origin to a few associated clinical applications and equipment. This facilitates the sharing of clinical data and meaningful online clinical conversations between doctors, other clinical experts, and patients. However, the ability to identify people with skin conditions who are more likely to develop skin illness has led to the widespread use of this method as a tailored reconnaissance strategy [3].

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Another imaging modality that improves diagnostic precision and may lower human mortality is dermoscopy. High-goal images produced by dermoscopy reveal additional skin features. Skilled dermatologists examine these images using a visual analysis. This method takes care and skill and takes up a significant portion of the day. Skin lesion identification can be done quickly and accurately by dermatologists using PC Helped Analysis (PC Assisted Design) frameworks. The four main phases of a computer-aided design framework are groupings, include extraction, divisions, and picture pre-handling.

It is basic to take note of that each step altogether affects the arrangement execution of the whole computer aided design framework. Sore division, a huge move toward the computer aided design framework for precisely distinguishing skin sores, is made testing by the skin sores wide changes in size, variety, surface, and area in dermoscopic pictures. Likewise, extra qualities, for example, hair, veins, black casings, ruler marks, air bubbles, variety light, and injuries can be challenging to distinguish and arrange when air bubbles are available. Subsequently, to accomplish high determination execution, powerful calculations should be utilized in each step [4].

Prior to going with choices that would affect the strength of patients, clinical doctors can perceive and arrange skin sores in pictures utilizing AI calculations [5]. Various examinations inspected different AI ways to deal with disease finding. Most of these examinations used prepared classifiers in light of an assortment of hand-created picture highlights. Most of AI techniques require a lot of computational time for precise conclusion, and their presentation on the chose qualities of the malignant district [6].

For the robotized recognizable proof of different types of skin illnesses, profound learning strategies including Convolutional Brain Organizations (CNNs) have become significant. In applications for picture characterization, profound learning has created amazing outcomes. To get around the absence of information and lessen how much memory and calculation expected for picture order assignments, move learning and information increase are utilized. Academicians have as of late involved semantic division capacities in CNN engineering models to separate pictures of skin sores.

The multiclass skin injury location and grouping using half breed highlight choice in light of Profound Convolutional Brain Organization (DCNN) is then presented in this review.

The rest of the work is organized as follows: The different examinations on skin sores and illnesses are talked about in Segment II. Segment III portrays a multiclass skin sore discovery and characterization technique in view of DCNN crossover highlights choice. In area IV, the introduced approach's outcome examination is illustrated. In segment V, this examination is at last closed.

2. LITERATURE SURVEY

It is important to remember that every stage has an overall impact on how the computer-aided design framework is classified and executed. A multi-highlight extraction technique based on profound learning is provided by Samia et al. [7] for the characterization of skin injuries in Sore Division. The researchers of this study evaluated the effectiveness of using 24 AI classifiers and 17 frequently used pre-prepared CNN models as element extractors to categorize skin lesions from two different datasets: PH2 (Pedro Hispano) and ISIC (Global Skin Imaging Cooperation) 2019. The results also show that our method outperforms comparable ones on the PH2 datasets with a high degree of precision.

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V. Srividhya a V et. al. [17] utilizes profound learning brain organizations to show vision based skin injuries discovery and grouping. Utilizing superior execution picture based AI calculations to change the power level during the pre-handling process, this exploration has fostered an advanced methodology for recognizing skin malignant growth. Division and component extraction from the skin sore district of interest are the accompanying stages in this methodology. Pictures from open-source data sets like DermIS and DermQuest are utilized in this strategy. Edge location and separating are essential for the preprocessing. The coordinated machine vision melanoma recognition framework's ID productivity was fundamentally upgraded

Amirreza Mahbod, et. al [18] shows Vision based Recognizable proof and Request of Skin addresses Skin Sore Plan Using Creamer Significant Mind Associations. To characterize skin sores, considered a PC framework coordinates improved profound highlights from some notable CNNs and from different degrees of deliberation. This framework is totally programmed. Profound element generators are AlexNet, VGG16, and ResNet-18, three pre-prepared profound models. Support vector machine classifiers are then prepared with the removed highlights. The classifier yields are consolidated in a last move toward produce an order.

Jordan Gab, et. al. [19] utilizes profound figuring out how to order multimodal skin sores. A five-class grouping test that was illustrative of a true clinical setting and a parallel characterization task for examination with past investigations are utilized by the creators to assess this strategy. A new dataset with 2917 cases was utilized for the trials, every one of which incorporates patient metadata, a perceptible picture, and a dermatoscopic pictures. The results showed that in both paired melanoma recognition and multiclass characterization, our multimodal classifier outflanked a standard classifier that just uses a solitary plainly visible picture. Be that as it may, in light of the fact that it just included cases with an obsessive determination, this study shows the typical confirmation predisposition.

Ilker et. al. [20] offers AI Calculations for Skin Sore Order. The objective of this review is to make a choice emotionally supportive network that ought to make it simpler for specialists to decide, which utilizations AI to

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pre-order the skin sores into three classes: melanoma, unusual, and typical. This exploration, which utilizes four different AI techniques, centers around skin sores that depend on PH2 datasets of dermoscopic pictures.[21][22]

Different exploration works have been depicted for skin sore arrangement and discovery utilizing various types of datasets. Anyway those approaches are precise for single injury identification yet for various skin sore discovery they are not exact, tedious and enormous datasets are required. Thus to address these issues, multiclass skin injury location and characterization is introduced where blend of two well known datasets to be specific HAM1000 and SIIMs ISIC 2020 is utilized..

3. MULTICALSS MEMBRANE GASH DETECTION AND CLASSIFICATION

In light of Profound Convolutional Brain Organization (DCNN), this review discusses Multiclass Skin Injury Discovery and Arrangement utilizing Half and Half Component Choice. The introduced model's design is displayed in Fig. 1. This work uses two datasets: the SIIM ISIC2020 challenge dataset and HAM10000, with the ultimate goal of the trial methodology. Both datasets accommodate the accompanying subtleties: "Human Against Machine (HAM) with 10,000 preparation pictures" is one of the largest datasets, and it is available to the general public as the "HAM1000 Set."

The inquiry photographs refer to the patient's skin images in order to determine whether or not they have a skin sore condition. In the unlikely event that they have an infection related to a skin injury, our technology will identify and treat it. The photo will be identified as having sound skin if it shows no signs of a skin sore condition. The datasets perform three distinct tasks: quality discovery, illness characterization, and injury division. More than 10,000 images from seven different classes make up this dataset for the grouping tasks. Identification systems necessitate pre-handling of the raw data since it may contain noise. Images of skin lesions are frequently accompanied by disturbances, such as hair, skin surface light reflection,

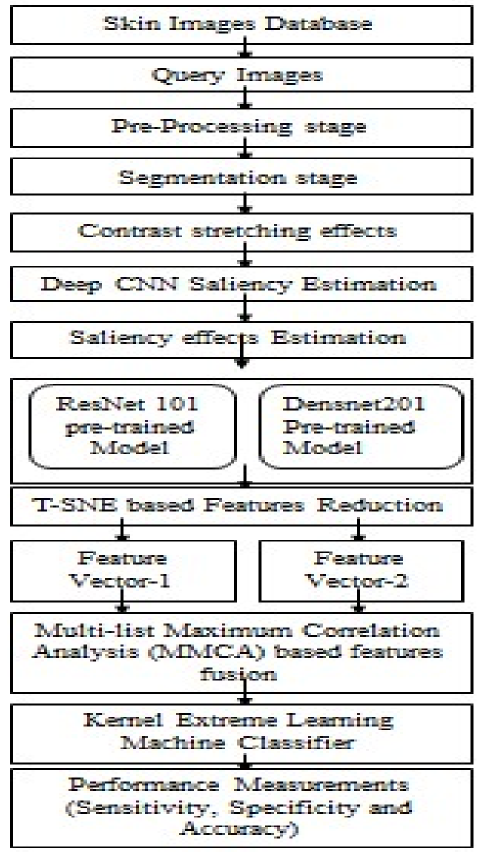

Fig. 1: The Architecture Of Presented Model

Erroneous placement of cutaneous lesions may be caused by disturbances such as hair. Pre-handling pertinent images should be completed using techniques including standardization, limitation, variety revision, hair expulsion, vignette evacuation, picture smoothing, and contrast alteration in order to eliminate or lessen disturbances. A well-designed pre-handling assignment setup would result in increased accuracy. The first stage completes the cycles of configuration transformation and location of interest (return on initial capital investment) discovery. The formal hat separating method is used to discern the dermoscopy images of thick and dim hair after the RGB (Red Green Blue) image is converted to a grayscale structure. There is a significant difference between the information and the result photos based on the outcomes of the past cycles.

$$Z_w = Gob - G \quad (1)$$

The end capability is indicated by o, G represents the info grayscale picture, while b represents the grayscale planning part. At last, the close by pixel values replace the hairline pixels during the composition cycle.

Albeit the division stage gives off an impression of being the straightforward, it is yet a significant interaction. To guarantee that clinical element division and the making of highlights utilized for arrangement can both have an

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effect by the division of skin injuries. The foundation should be separated from the sore for this situation, the skin and different relics during this stage. By and large, the partition shows up as a twofold picture (otherwise called a double veil), is a typical method for showing the division. In a twofold picture, names are given to the sore locale and the eliminated foundation skin. After the injury locale was isolated from the foundation, the clinical highlights would be fragmented. Different worldwide qualities, like boundary anomalies and data about deviation, would be uncovered by the division.

One of the fundamental necessities for assessing picture quality is contrast upgrade. The improvement of picture quality over the first picture is the principal objective of this step. The essential objective is to expand the injury area's differentiation so the locale of interest might be removed with basic (return for money invested). The expression "neighborhood variety controlled histogram power values" (LCcHIV) alludes to a half and half difference extending approach. Subsequent to creating a histogram of the information picture, this strategy joins the change values to recognize the impacted pixels. A further refinement process called Histogram Evening out (HE) is applied to the created change esteem based picture. A wellness capability is utilized to later increment and change the force values as per the injury and foundation districts. To start with, the accompanying advances are taken to ascertain the picture's Hxy histogram:

$$h_f(k) = O_j \quad (2)$$

Where f demonstrates the recurrence of events, Oj addresses the event of dark levels, and j ∈ 0, 1, and 2 . . . K-1 and hf (k) is the histogram of a picture Hxy. Condition shows the scope of tainted pixels, which is resolved utilizing hf (k).

$$\widetilde{h_f(k)} = h_f(k)[I_j]_{k1,kn} \quad (3)$$

Where j signifies the pixel values and Ij means the contaminated locale fix. The whole contaminated locale is indicated by the hf (k), and the factors of k1 to kn address the size of the impacted district. Later, the condition is utilized to compute the change of the whole picture.

$$\sigma^2(H_{xy}) = \frac{1}{MN}\sum_{i=0,j=0}^{M-1,N-1}(H_{ij})^2 - \mu^2 \quad (4)$$

Where $\mu = \frac{\sum_{i=0,j=0}^{N-1,M-1}(H_{ij})}{MN}$ (4)

A few associations are eliminated in the ResNet101 CNN Model, along with the use of establishing direct associations between the layers. ResNet101 uses "bottleneck" building blocks to reduce the boundaries. The organization consists of five convolutional blocks: the principal structure block, Conv2, consists of three blocks, each of which contains three convolutional layers. Conv2 addresses the first convolutional layer, Conv1. The third convolutional layer is composed of four separate components. 23 and 3 structural building blocks separately, the fourth and fifth convolutional layers. The FC (Completely Associated) layer, which is used for categorization, makes up the last layer.

DenseNet201's highlights are all connected in sequential order. This design's first convolutional layer has a step of [2, 2] and a 7 × 7 channel size. This is followed by a maximum pooling layer with a 3 x 3 channel size. After that, a thick block is inserted, followed by a convolutional layer that is 1x1 or 3x3 in size for each thick block.

Seeing high-layered information and extending it into low-layered environments (like 2D or 3D) is the fundamental use of T-SNE. As CNN networks are integrated, it proves to be quite beneficial. T-Dispersed Stochastic Neighbour Implanting is a non-direct, solitary approach to analysing and visualizing high-layered information (T-SNE). A component vector is a logical list of the mathematical characteristics of observed anomalies. It is intended as information highlights by an expectation-making AI machine. People are able to make decisions by analysing subjective data. In this analysis, the dataset for the multiclass characterization is first balanced using an information expansion phase. For this reason, the corresponding duties are completed: the initial image has been rotated, shifted to the left, and rendered.

ResNet101 and DenseNet201 are two deep learning models that are used once the skin classes are adjusted. These models are pre-prepared. The Multiset Greatest Relationship Investigation (MMCA) method is applied for highlight combining. Part Outrageous Learning Machine (KELM) further increases the power of Outrageous Learning Machine (ELM) by transforming data that is straight-forwardly non-divisible into information that can be directly detached in a low-layered space. To define combined highlights, we use the Part Outrageous Learning Machine (KELM) for Multiclass skin injuries order. The KLEM calculation entirely groups together Melanocytic Nevus (NV), Melanoma (MEL), Basal Cell Carcinoma (BCC), Actinic Keratosis (AK), Harmless Keratosis Injury (BKL), Dermatofibroma (DF), Squamous Cell Carcinoma (SCC), and Vascular Sore (VASC). The three dimensions of responsiveness, particularity, and exactness are used to rate the presentation of the design.

4. RESULT ANALYSIS

Multiclass membrane Gash location and grouping utilizing mixture highlight choice in view of Profound Convolutional Brain Organization is executed in this work. The outcome examination of the introduced Multiclass skin sore order utilizing half and half component determination in light of Profound CNN is exhibited in this investigation. The exploratory examination is performed on two datasets in particular ISIC 2020 test and HAM1000 Dataset. The presentation of introduced designs is estimated utilizing disarray grid boundaries to be specific: Genuine Positive (TP),

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Genuine Negative (TN), Bogus Positive and Misleading Negative (FN) which are characterized as follows:

TP: if an instance is actually positive despite being correctly classified as positive.

TN: If an instance is actually negative and correctly classified as negative.

FP: if an instance is incorrectly categorized as positive when it is actually negative.

FN: if an instance is incorrectly categorized as negative but is actually positive.

Accuracy: It is given as the ratio of instances correctly detected to the total number of instances.

$$Accuracy = \frac{TP + TN}{TP + FP + TN + FN} \quad (5)$$

Sensitivity: It is sometimes referred to as True Positive Rate (TPR), and it is referred to as the ratio of actual positive cases to true positive cases.

$$Sensitivity = \frac{TP}{TP + FN} \quad (6)$$

Specificity: The definition is given as the ratio of true negative instances to actual negative instances (FP + TN).

$$Specificity = \frac{TN}{TN + FP} \quad (7)$$

The Fig. 2 shows the confusion matrix.

ACTUAL CLASS \ PREDICTED CLASS	MEL	NV	BCC	AK	BKL	DF	VASC	SCC
MEL	95%			2%				1%
NV	9%	97%				3%		
BCC	3%	2%	94.6 %				5%	
AK				96%	4%			2%
BKL			1%		97%			3%
DF		3%		1%		96.7 %		
VASC					4%		95.4 %	
SCC	3%			1%				97.3 %

Fig. 2: Confusion Matrix

The Table 1 represents the performance metrics of presented architecture and presented architecture is compared with ML approaches.

Table 1: Performance Metrics Evaluation

Performance Metrics	ML based Multiclass skin lesion classification approach	Deep Convolutional DCNN approach
Sensitivity (%)	91.5	96.8
Specificity (%)	89.8	95.6
Accuracy (%)	93.3	97.8

The responsiveness analysis of the proposed DCNN approach and the ML-based strategy is displayed in Fig. 3. Figure 3 makes it clear that introduced engineering is more conscious than ML-based models.

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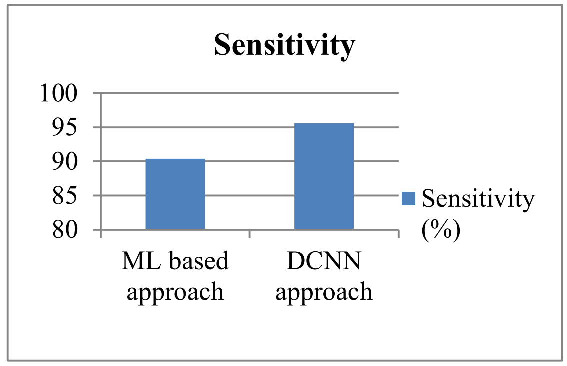

Fig. 3: A Comparitive Graph For **SENSITIVITY**

Figure 4 presents a comparison of specificity between the CNN approach and the machine learning-based approach.

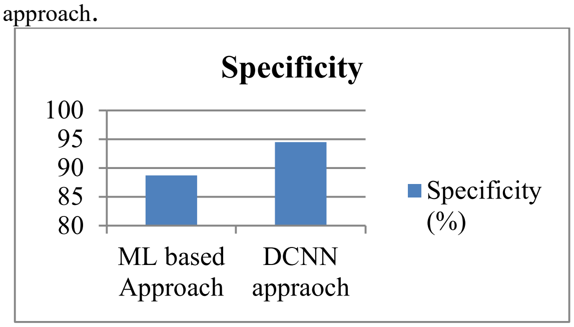

Fig. 4: A Comparitive Graph For Specificity

Therefore, the DCNN technique has high sensitivity than ML based approaches. The accuracy comparison between the given and ML-based techniques is displayed in Figure 5.

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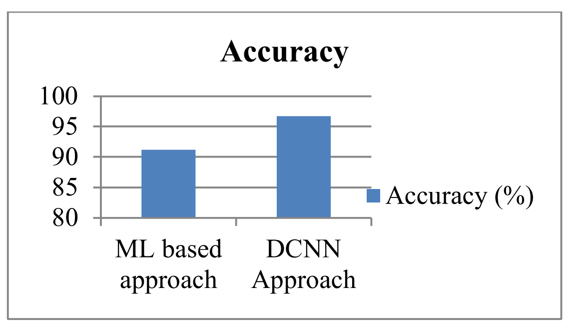

Fig. 5: *Accuarcy Comaprison Between Ml Based And Presented Cnn Appraoches*

The discoveries clarify that the DCNN-based half and half component choice methodology used to recognize and characterize multiclass skin sores precisely characterized these injuries.

5. CONCLUSION

This study illustrates multiclass video slice location and characterization using cross breed highlight identification in the context of a deep convolutional brain network. Two datasets, namely HAM1000 and ISIC2020challenge, are used in this design. ResNet101 and Dense201, two CNN models, are used to increase the introduced engineering's grouping accuracy.
. The many kinds of skin sores are partitioned into classes utilizing KLEM. Responsiveness, exactness, and explicitness are utilized to gauge the exhibition of the design that was introduced. The introduced design has really identified and ordered the skin injuries. Contrasted with ML based designs, introduced engineering have better execution regarding responsiveness, precision, and explicitness. Later on, profound learning based half breed classifier approach will be introduced to acquire 100 percent multiclass skin injury location and grouping exactness and to give appropriate conclusion to skin sore sicknesses.

REFERENCES

[1] Mustafa Qays Hatem, "Skin lesion classification system using a K-nearest neighbor algorithm", Visual Computing for Industry, Biomedicine, and Art (2022) 5:7, /doi.org/10.1186/s42492-022-00103-6

[2] G. Reshma, Chiai Al-Atroshi, Vinay Kumar Nassa, B.T. Geetha, Gurram Sunitha, Mohammad Gouse Galety and S. Neelakandan, "Deep Learning-Based Skin Lesion Diagnosis Model Using Dermoscopic Images", Intelligent Automation & Soft Computing, IASC, 2022, vol.31, no.1 DOI:10.32604/iasc.2022.019117

[3] Puneet Thapar, Manik Rakhra, Gerardo Cazzato, and Md Shamim Hossain, "A Novel Hybrid Deep Learning Approach for Skin Lesion Segmentation and Classification", Hindawi Journal of Healthcare Engineering, Volume 2022, Article ID 1709842, 21 pages, doi.org/10.1155/2022/1709842

[4] Wessam Salma & Ahmed S. Eltrass, "Automated deep learning approach for classification of malignant melanoma and benign skin lesions", Multimedia Tools and Applications, 2022, Springer, doi.org/10.1007/s11042-022-13081-x

[5] Jwan Najeeb Saeed, Subhi R. M. Zeebaree, "Skin Lesion Classification Based on Deep Convolutional Neural Networks Architectures", Journal of Applied Science and Technology Trends Vol. 02, No. 01, pp. 41 –51 (2021), doi: 10.38094/jastt20189

[6] Muhammad Attique Khan, Muhammad Sharif, Tallha Akram, Robertas Damaševiˇcius, and Rytis Maskeli unas, "Skin Lesion Segmentation and Multiclass Classification Using Deep Learning Features and Improved Moth Flame Optimization", Diagnostics 2021, 11, 811, doi.org/10.3390/diagnostics11050811

[7] Samia Benyahia, Boudjelal Meftah, Olivier Lézoray, "Multi-Features Extraction Based on Deep Learning for Skin Lesion Classification", 2021 Elsevier, HAL Id: hal-03457466, doi: hal.archives-ouvertes.fr/hal-03457466

[8] Zahraa E. Diame A, Maryam N. Al-Berry A, Mohammed A.-M. Salemb, Mohamed Roushdy, " Autoencoder Performance Analysis Of Skin Lesion Detection", Journal Of Southwest Jiaotong University, Vol. 56 No. 6 Dec. 2021 Issn: 0258-2724 Doi : 10.35741/Issn.0258-2724.56.6.82

[9] Mario Fernando Jojoa Acosta, Liesle Yail Caballero Tovar, Maria Begonya Garcia-Zapirain and Winston Spencer Percybrooks, "Melanoma diagnosis using deep learning techniques on dermatoscopic images", *BMC Med Imaging* 2021, 21:6, Open Access, doi.org/10.1186/s12880-020-00534-8

[10] Mohamed Yacin Sikkandar Bader Awadh Alrasheadi, N. B. Prakash, G. R. Hemalakshmi, A. Mohanarathinam and K. Shankar, "Deep learning based an automated skin lesion segmentation and intelligent classification model", Journal of Ambient Intelligence and Humanized Computing, 2020, doi.org/10.1007/s12652-020-02537-3

[11] Atharva Jibhakate, Pranav Parnerkar, Sahil Mondal, Vastav Bharambe, Shamla Mantri, "Skin Lesion Classification using Deep Learning and Image Processing", Proceedings of the Third International Conference on Intelligent Sustainable Systems [ICISS 2020] IEEE Xplore Part Number: CFP20M19-ART; ISBN: 978-1-7281-7089-3

[12] Noortaz Rezaoana, Mohammad Shahadat Hossain, Karl Andersson, "Detection and Classification of Skin Cancer by Using a Parallel CNN Model", 2020 IEEE International Women in Engineering (WIE) Conference on Electrical and Computer, Engineering (WIECON-ECE)

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

[13]Honey janoria; jasmine minj; pooja patre, “classification of skin disease from skin images using transfer learning technique classification of skin disease from skin images using transfer learning technique”, 2020 4th international conference on electronics, communication and aerospace technology (iceca), 2020, doi: 10.1109/ICECA49313.2020.9297567

[14]Gourav Chowdary, Neeraj Kumar Toppo, Debanjan Das, “Skin Lesion Diagnosis in Healthcare-Cyber Physical System”, 2020 IEEE International Conference for Innovation in Technology (INOCON), Bengaluru, India, Nov 6-8, 2020, 978-1-7281-9744-9/20,

[15] Kemal Polat, Kaan Onur Koc, “Detection of Skin Diseases from Dermoscopy Image Using the combination of Convolutional Neural Network and One-versus-All”, Journal of Artificial Intelligence and Systems, 2020, 2, 80-97 https://iecscience.org/journals/AIS ISSN Online: 2642-2859

[16] Yutong Xie , Jianpeng Zhang , Yong Xia , and Chunhua Shen, “Mutual Bootstrapping Model for Automated Skin Lesion Segmentation and Classification”, IEEE Transactions On Medical Imaging, Vol. 39, No. 7, July 2020

[17] V. Srividhya a,K.Sujatha, R.S. Ponmagal, G.DurgadevicL. Madheshwaran V, “Vision based Detection and Categorization of Skin lesions using Deep Learning Neural networks”, Procedia Computer Science, Volume 171, 2020, Pages 1726-1735, doi: 10.1016/j.procs.2020.04.185

[18] Amirreza Mahbod, Gerald Schaeferz, Chunliang Wang, Rupert Eckery, Isabella Ellinger, “Skin Lesion Classification Using Hybrid Deep Neural Networks”, ICASSP 2019, 978-1-5386-4658-8/18, 2019 IEEE.

[19] Jordan yap, william yolland, philipp tschandl, “multimodal skin lesion classification using deep learning”, experimental dermatology, 2018; 27:1261–1267, wileyonlinelibrary.com/journal/exd

[20] ilker ali ozkan, murat koklu, “skin lesion classification using machine learning algorithms”, international journal of intelligent systems and applications in engineering, issn:2147-6799, 2017, doi: 10.18201/ijisae.2017534420

[21] M V Ganeswara Rao, P Ravi Kumar, T Balaji, “ A High Performance Dual Stage Face Detection Algorithm Implementation using FPGA Chip and DSP Processor “ , Journal of Information Systems and Telecommunication (JIST),2022,pp 241-248, doi: 10.52547/jist.31803.10.40.241

[22]T Balaji, P.Ravi Kumar, M.V.Ganeswara Rao, Geetha Devi Appari, “Creating The Best Directed Random Testing Method To Minimize Interactive Faults- Empirical Perspective”, Journal Of Theoretical And Applied Information Technology, 2023,101(7),Pp-2540-2546.