IJARSCT
ISSN (Online) 2581-9429
International Journal of Advanced Research in Science, Communication and Technology (IJARSCT)
International Open-Access, Double-Blind, Peer-Reviewed, Refereed, Multidisciplinary Online Journal
Impact Factor: 7.301
Volume 3, Issue 1, July 2023

Detection of Melanoma Skin Cancer Disease using AI based Approaches for Medical Image Processing - A Study

Mithun D Souza[1], Sunil Kumar S[2], Sai Sasank Majeti[3], Dr. Jayashree Nair[4], Srinivas BL[5]
Assistant Professor, Department of Information Technology, AIMS Institutes, Bangalore, India[1,2,3]
Associate Professor, Department of Information Technology, AIMS Institutes, Bangalore, India[4]
Assistant Professor, Department of Information Technology, AIMIT, St. Aloysius College, Mangalore, India[5]
mitundsouza@gmail.com[1], sksmcafaculty2022@gmail.com[2], sasank.majeti@gmail.com[3],
nair.jayshree@gmail.com[4] srinivasbl.vas@gmail.com[5]

Abstract: *Malignant melanoma, often known as melanoma, is a form of skin cancer that occurs when melanocyte cells that have been harmed by prolonged exposure to UV radiation begin to grow uncontrollably. Although less frequent than certain other types of skin cancer, it is more hazardous because, if not identified and treated at its earliest stages, it quickly metastasizes. Due to their challenging and subjective human interpretation and extremely complex and expensive diagnosis, dermatological diseases rank among the most serious medical problems of the twenty-first century. When it comes to lethal illnesses like melanoma, early detection is crucial for assessing the likelihood of recovery. We think the use of automated approaches will aid in early diagnosis, particularly when a batch of photos has a variety of diagnoses. Therefore, in contrast to traditional medical personnel-based detection, an effort is made to list out the feasible approaches that are already defined to identify the melanoma skin disease. This study on various existing approaches will provide insights on the technologies available in the current era to identify this deadliest disease at the earliest possible time.*

Keywords: Melanoma, Malignant, Skin Cancer, Image Processing.

I. INTRODUCTION

Since the skin is the outermost layer of our bodies, it is likely to be in contact with contaminants like UV radiation, bacteria, dust, and pollution. Any skin issue could be brought on, and gene instability can also produce conditions related to skin, which complicates matters further. The two primary layers of human skin are the epidermis and dermis. Three different cell types make up the epidermis, or top layer of skin: melanocytes, which give skin its color and protect it from injury; SQUAMOUS cells, which are flat and scaly on the surface; and basal cells, which give skin its round shape. It is impossible to effectively predict the course of the disease or treat it because the diagnostic classification does not currently reflect the wide range of the condition. Additionally, cancer cells are usually only found and treated after they have mutated and spread to various internal organs of the body. Currently, therapies and treatments are not very effective. The fact that people tried to treat the illness at home without first realizing how bad it was and that this could lead to new types of skin rashes or even deterioration of the ailment may have contributed to the disease's increased danger.

II. DETECTION OF SKIN CANCER

Skin cancer detection using medical image processing is a rapidly growing field with the potential to improve the early detection and diagnosis of skin cancer.

A. Commonly employed steps to detect skin cancer using image processing

The basic steps involved in skin cancer detection using image processing are:

- **Image acquisition:** The first step is to acquire a high-quality image of the skin lesion. This can be done using a variety of methods, including dermoscopy, reflectance confocal microscopy, and optical coherence tomography.
- **Preprocessing:** The acquired image is then preprocessed to remove noise and artifacts. This can be done using techniques such as filtering, contrast enhancement, and normalization.
- **Segmentation:** The next step is to segment the skin lesion from the surrounding tissue. This can be done using a variety of methods, including thresholding, region growing, and edge detection.
- **Feature extraction:** Once the skin lesion has been segmented, features are extracted from the image. These features can be based on the lesion's shape, texture, color, and other characteristics.
- **Classification:** The extracted features are then used to classify the skin lesion as benign or malignant. This can be done using a variety of machine learning algorithms, such as support vector machines, neural networks, and decision trees.

B. Advantages of Medical Image Processing for Skin Cancer Detection

The use of medical image processing for skin cancer detection has several advantages.

- It can be used to automate the process of diagnosing skin cancer, which can free up time for dermatologists to focus on more complex cases.
- It can be used to improve the accuracy of diagnosis, especially for early-stage skin cancers.
- It can be used to provide more objective and reproducible results than traditional methods of diagnosis.

C. Challenges in Medical Image Processing for Skin Cancer Detection

- One challenge is that the accuracy of the technique can vary depending on the quality of the image.
- Another challenge is that the technique can be computationally expensive, which can limit its use in resource-limited settings.

Despite these challenges, the use of medical image processing for skin cancer detection is a promising area of research. As the technology continues to develop, it is likely to play an increasingly important role in the early detection and diagnosis of skin cancer.

D. Commonly used Skin Cancer Detection Techniques

Some of the most common image processing techniques used for skin cancer detection are:

- **Thresholding:** This technique is used to convert an image into a binary image, where each pixel is either black or white. This can be done by setting a threshold value, and then assigning all pixels below the threshold value to be black, and all pixels above the threshold value to be white.
- **Region growing:** This technique is used to identify and segment regions of interest in an image. This is done by starting with a seed pixel and then iteratively adding neighboring pixels to the region if they meet certain criteria.
- **Edge detection:** This technique is used to identify the edges of objects in an image. This is done by finding the points in the image where the intensity changes sharply.
- **Feature extraction:** This technique is employed to perform feature extraction from an image that can be considered to classify the image. These features can be based on the image's shape, texture, color, and other characteristics.
- **Classification:** This technique is used to classify an image into a particular category. This is done by using a machine learning algorithm to learn the relationship between the extracted features and the image's category.

The choice of image processing techniques used for skin cancer detection will depend on the specific application. However, the techniques listed above are some of the most common and effective techniques used for this purpose. In this study, we have analysed various approaches developed for the early diagnosis of melanoma using medical image processing.

III. LITERATURE REVIEW

A deep learning-based "You Only Look Once (YOLO)" approach is presented by Banerjee, S. et al.[1] in 2020. It focuses on utilizing DCNNs for recognizing melanoma through dermoscopic imaging and digital photos and offers quicker and more accurate results than traditional CNNs. This network forecasts the bounding box of the identified object as well as the class confidence score based on the position of the object as indicated in the cell. This method's strength comes from the incorporation of a few original concepts, including two-phase segmentation, which incorporates graph theory along with the concept of minimal spanning tree and approximation based on L-type fuzzy numbers, as well as mathematical feature extraction that extracts the actually affected portion of the cancerous region.

An approach to identifying melanoma using image processing has been proposed by M. Julie T. et al. [2] (2021). The system incorporates a process that includes preprocessing, segmentation, feature extraction, and classification. The Sobel process, Otsu's approach, ABCD rule, and K-means with a support vector machine (SVM) classifier are the algorithms that are suggested for each phase. When combined, these algorithms provide reasonable accuracy with respect to the lesion's size, shape, color, and texture. This causes the region of interest to be extracted and used for computerized surgery. The results are produced using the PH2 dataset.

Kritika S. R. et al. [3] (2020) create a multiclass deep learning model to distinguish between healthy skin and skin that has a disease, as well as to classify skin diseases into their primary classes, such as basal cell cancer, actinic keratoses, melanocytic nevi, benign keratoses-like lesions, vascular lesions, and dermatofibroma. In this method, machine learning is combined with deep learning to train the model. The machine self-learns, divides the supplied data into levels of prediction, and provides accurate findings in a very short amount of time, encouraging and supporting the growth of dermatology. The convolutional neural network (CNN) algorithm is the one we utilized to classify the images.

Two issues were addressed in the work Arjun K. P. et al. [4] (2021) proposed, the first of which was the imbalance of datasets that is typical in supervised learning approaches, and the second of which was the prediction of skin melanoma. In other words, there are two classes of data in a skin cancer binary classification problem: malignant melanoma and benign melanoma. Melanoma is a highly rare data type in all publicly accessible datasets. Here, utilizing data augmentation techniques to provide various images to balance the unbalanced class, we find a general solution to the imbalanced dataset problem. A neural network (NN)-based model is then used to learn the ABCDE features of skin melanoma, which pulls the features from the photos of skin lesions regardless of a person's skin color, age, gender, etc. The proposed model generated an accuracy of 96.6% when used with the ISIC dataset. When comparing the results of our work to recent ones, we found that our work performed well in the specificity and simplicity categories, scoring 98.39% and 94.06%, respectively.

In contrast to traditional medical personnel-based detection, Vijayalakshmi M. M. [5] (2019) introduced a fully automated approach to dermatological illness recognition from lesion photos. Our model is created in three stages, which include data gathering and augmentation, model construction, and prediction. With this method, skin cancer can be accurately predicted and classified as either malignant or non-malignant melanoma. With the help of image processing technologies, many AI techniques, including Convolutional Neural networks and Support Vector machines, are combined to create a better structure and achieve an accuracy of 85%.

Through the extraction of texture and color features, Pallavi B. et al. [6] (2019) present an image pattern classification to recognize skin illness in photos. Images of both healthy and pathological conditions are initially gathered and pre-processed using PCA and multilevel Otsu thresholding to turn the images grayscale. Also included in the post-processing are techniques for erosion and dilation as well as clever edge recognition for quantization. Following the extraction of shape, color, and texture features from the photos, a support vector machine classifier is used to categorize the images. To evaluate acceptable features and identify distinguishing traits for disease detection, a combination of many features is used. The shape feature has the lowest accuracy, and the texture feature has the highest accuracy when only one characteristic is employed. The maximum classification accuracy is obtained when texture and color feature extraction are combined.

Alwakid, G. et al. [7] (2022) suggest using DL as a way of precisely extracting a lesion zone. The quality of the image is first improved using Enhanced Super-Resolution Generative Adversarial Networks (ESRGAN). Then, regions of interest (ROI) are separated from the entire image using segmentation. We employed data augmentation to deal with the data discrepancy. The image is then analyzed with a convolutional neural network (CNN) along with a modified version of Resnet-50 to categorize skin lesions. Seven different types of skin cancer were selected at random for this research from the HAM10000 dataset. The suggested CNN-based Model significantly surpassed the outcomes of the earlier study with an accuracy of 0.86, precision of 0.84, recall of 0.86, and an F-score of 0.86. The study's conclusion offers patients and medical professionals an enhanced automated technique for diagnosing skin cancer.

In order to address issues like artifacts (hair, gel bubble, ruler marker), distorted boundaries, poor contrast, and variable shape and size of the lesion images, Reshma G. et al. [8] (2022) proposed intelligent multilevel thresholding with deep learning (IMLT-DL)-based skin lesion segmentation as well as a classification model using dermoscopic images. The top-hat filtering and inpainting approaches are primarily used in the described IMLT-DL model to pre-process the dermoscopic pictures. The regions that are infected are also identified using Mayfly Optimization (MFO) with multilevel Kapur'sthresholding-based segmentation approach. In addition, a useful set of feature vectors is produced using an Inception v3-based feature extractor. A gradient-boosting tree (GBT) model is used to complete the classification process. The International Skin Imaging Collaboration (ISIC) dataset is employed to test the efficiency of the proposed model, and several evaluation metrics are applied to the experimental results. The experimental results show that the suggested IMLT-DL model works better than the current approaches by reaching a higher accuracy of 0.992.

In order to categorize skin cancer, Vatekar K. et al. [9] (2023) suggested an automated classification approach based on image processing methods. This method uses convolutional neural networks to identify and categorize different types of cancer based on previously collected clinical imaging data. CNNs are utilized to create a CNN model for skin cancer diagnosis that has an accuracy of over 80% and a false-negative rate of less than 10% when making predictions. The skin cancer prediction model's exceptional testing accuracy of 98% demonstrates how well-refined it is at spotting skin cancer from photos. Deep learning algorithms are used to identify and categorize skin lesions as benign or malignant using a large dataset of photos of skin lesions.

On the basis of datasets obtained from the most recent publicly available "Skin Lesion Analysis toward Melanoma Detection" grand challenges of ISIC 2018, Aldwgeri A. et al. [10] (2019) provide prospective skin lesion categorization solutions. Convolutional neural networks (CNN) and transfer learning are used in this method to improve skin classification. VGG-Net, ResNet50, InceptionV3, Xception, and DenseNet121 were among the pre-trained models used. Additionally, a number of balancing strategies, including weight balancing and data augmentation, are taken into consideration. The heavy class imbalance is studied as a crucial issue for this dataset. In order to classify the seven various forms of skin lesions, an ensemble technique is examined by mixing and averaging numerous CNN designs. When compared to the live scoreboard for the ISIC 2018 challenge, the proposed frameworks show encouraging outcomes.

InSiNet, a deep learning-based convolutional neural network to detect benign and malignant lesions, was proposed by Reis, H. C., et al. [11] in 2022. The International Skin Imaging Collaboration's HAM10000 samples from 2018 (ISIC 2018), 2019 (ISIC 2019), and 2020 (ISIC 2020) are used to test the method's effectiveness. The suggested methodology was compared to existing machine learning methods such as ResNet152V2, GoogleNet, RBF-support vector machine, DenseNet-201, EfficientNetB0, logistic regression, and random forest in terms of computation time and accuracy. The outcomes demonstrate that the InSiNet framework outperformed the alternative methods, obtaining accuracy levels of 94.59%, 91.89%, and 90.54% in the relevant ISIC 2018, 2019, and 2020 datasets. In addition to conventional methods, deep learning algorithms can provide solid results because they remove the human element from diagnostics.

An effective convolutional neural network (CNN) model that precisely pinpoints skin cancer issues was proposed by Rajput G. et al. [12] in 2021. Although HAM10K is the dataset used for the classification problem, the samples within each class are quite unbalanced, which contributes to reduced training accuracy. To solve this issue, the AlexNet model is modified for the HAM10K data classification. With this method, an activation function that solves the vanishing gradient issue is proposed, and it is tested on the dataset at various benchmark architectures. The results demonstrate improved accuracy for customized CNN architecture, with HAM10K achieving 98.20% accuracy compared to the

IJARSCT
ISSN (Online) 2581-9429
International Journal of Advanced Research in Science, Communication and Technology (IJARSCT)
International Open-Access, Double-Blind, Peer-Reviewed, Refereed, Multidisciplinary Online Journal
Impact Factor: 7.301
Volume 3, Issue 1, July 2023

current state-of-the-art activation function. Additionally, results for precision, recall, and F-score are improved and are also 98.20%.

In order to improve medical professionals' visual perception along with diagnostic skills to distinguish benign from malignant lesions, Thapar, P. et al. [13] (2022) provide a reliable approach for detecting skin cancer by considering dermoscopy images. Dermoscopy images have been employed to segment the skin lesion region of interest (RoI) using swarm intelligence (SI) algorithms, and the Grasshopper Optimization Algorithm (GOA) was implemented to extract features from the RoI that produced the best segmentation results. Using CNN and three data sets—the ISIC-2017, ISIC-2018, and PH-2 data sets—the skin lesions are divided into two groups. Results from the proposed segmentation and classification approaches are assessed for classification precision, sensitivity, specificity, F-measure, precision, MCC, dice coefficient, and Jaccard index; on average, classification accuracy is 98.42%, precision is 97.73%, and MCC is 0.9704%.

By employing melanocytic and nevus lesions as dividing lines, Ragab M. et al. [14] (2022) presented a unique method for segmenting dermoscopy pictures. This study proposes a brand-new classification scheme for lesions. This paper proposes a paradigm for segmenting inhomogeneous images based on level-set segmentation. By increasing the quantity of pixels utilized to represent hair and vessels, directed wavelet filters are capable of being used to eliminate artifacts. To distinguish the lesion from the surrounding skin, the picture is enlarged, the threshold is lowered, and any additional morphological procedures are completed. An inventive technique for identifying and eliminating malignant hairs makes use of an improved leveling process. The adaptive sigmoidal function, which takes into account the severity of localized lesions, helps to identify the lesion from the surrounding skin. Although tested with 100 different dermoscopy photographs, which each showed either benign lesions, nevi, or metastatic melanoma, the model exhibits outstanding speed, accuracy, convergence, resilience to the contour start location, and noise interference. With a 94.4 percent true detection rate, a 3.62 percent false positive rate, and a 3.39 percent error rate, the suggested technique surpasses the alternative when tested using the Melanoma Skin Cancer Dataset.

A deep-learning-based strategy, using faster region-based convolutional neural networks (RCNN) and fuzzy k-means clustering (FKM), was used by Ragab M. et al.[15] (2022) to offer a fully automated method for segmenting cutaneous melanoma at its earliest stage. This method is put to the test using a variety of clinical photos in the hopes that it may aid dermatologists in the early detection of this fatal condition. Before employing the faster RCNN to produce the feature vector with a fixed length, it first preprocesses the dataset photos to reduce noise and illumination issues and improve the visual information. The melanoma-affected area of skin has then been divided into segments with varying sizes and borders using FKM. The results obtained demonstrate that the proposed technique improves upon the most recent techniques with an average accuracy of 95.40 and 93.1, respectively, demonstrating its robustness for skin lesion recognition and segmentation. The efficiency of the Proposed method is evaluated on the three standard datasets, particularly ISBI-2016, ISIC-2017, and PH2.

Name of the Algorithm	**Method Employed**	**Algorithm used**	**Data set used**	**Remarks**
Melanoma Diagnosis Using Deep Learning and Fuzzy Logic [1]	Deep Learning, Fuzzy Logic	You Only Look Once (YOLO)	PH2, the International Skin Imaging Collaboration (ISIC) 2019, and the International Symposium on Biomedical Imaging (ISBI) 2017	Jac grades of 79.84% for PH2, 86.99% for ISBI, as well as 88.64% for ISIC had been obtained utilising two-phase segmentation plus mathematical feature extraction.
Melanoma Detection on Skin Lesion Images [2]	Sobel process, Otsu's method, ABCD rule	K-Means & SVM Classifier	PH2	Outstanding accuracy in terms of the lesion's size, shape, colour, and texture values

IJARSCT
ISSN (Online) 2581-9429
International Journal of Advanced Research in Science, Communication and Technology (IJARSCT)
International Open-Access, Double-Blind, Peer-Reviewed, Refereed, Multidisciplinary Online Journal
Impact Factor: 7.301
Volume 3, Issue 1, July 2023

Skin Disease Detection using Machine Learning [3]	Data Gathering, DataPreprocessing& Enhancement, Training, Model Building, Model Evaluation, Graphical Analysis	Convolutional Neural Network (CNN)	Trained and Tested Sample (Skin Cancer Image)	Automatic computer-based detection produced a detection accuracy evaluation of 93.35 %.
Classification of Skin Melanoma Using Neural Network [4]	Analysis, Feature Extraction, Model Prediction, & Model Evaluation	Data augmentation, Neural Networks (NN) Model	International Skin Imaging Collaboration (ISIC Imbalance Dataset)	With 96.6% accuracy, 94.06% sensitivity, and 96.6% specificity, the challenge of skin cancer classification and an imbalanced set of data is answered.
Melanoma Skin Cancer Detection using Image Processing and Machine Learning [5]	Collection, Pre-processing, Segmentation and Feature Extraction, Designing of the Model and Training	Back Propagation, SVM & CNN	International Skin Imaging Collaboration (ISIC dataset)	An accuracy rate of 85% in predicting skin cancer and the capacity to distinguish between malignant and non-malignant melanoma skin cancer
Hybrid Diagnosis System forMalignantMelanomaDetection in Dermoscopic Images [6]	Acquisition, Pre-processing, Segmentation, Feature extraction, Classification	PCA, Multilevel Otsu Thresholding, Dilation and Erosion Techniques, Canny Edge Detection, SVM classifier	Trained and Tested Sample (Skin Cancer Image)	Feature extraction via texture and colour combination delivers the highest classification accuracy
Melanoma Detection Using Deep Learning-Based Classifications [7]	ESRGAN (Enhanced Super-Resolution Generative Adversarial Networks),Regions of Interest (ROI)	CNN and a modified Resnet-50	HAM10000 (Human Against Machine dataset)	Analysis of skin lesions can be used to efficiently and precisely identify seven distinct types of cancer, with an 85.3 percent and 85.98 percent–86 percent accuracy rate.
Deep Learning-Based Skin Lesion Diagnosis Model Using Dermoscopic Images [8]	Mayfly Optimization (MFO) with Multilevel Kapur'sThresholding, Inception v3, Gradient Boosting Tree (GBT)	Intelligent Multilevel Thresholding with Deep Learning (IMLT-DL)	International Skin Imaging Collaboration (ISIC) dataset	The proposed IMLT-DL model performs better than existing methods, achieving an accuracy of 0.992.
Skin Cancer Prediction using Deep Learning [9]	ImageNet, CNN	Convolutional Neural Networks (CNN)	Sample Dataset (large dataset of skin lesion images)	The false-negative rate remained below 10 % in prediction with a testing accuracy of 98% and a CNN model for skin cancer diagnosis with higher than 80% accuracy.

IJARSCT

ISSN (Online) 2581-9429

International Journal of Advanced Research in Science, Communication and Technology (IJARSCT)

International Open-Access, Double-Blind, Peer-Reviewed, Refereed, Multidisciplinary Online Journal

IJARSCT

Impact Factor: 7.301

Volume 3, Issue 1, July 2023

Ensemble of Deep Convolutional Neural Network for Skin Lesion Classification in Dermoscopy Images [10]	VGG-Net, ResNet50, InceptionV3, Xception and DenseNet121	Convolutional Neural Networks (CNN)	International Skin Imaging Collaboration (ISIC 2018) dataset	The seven various kinds of skin lesions were evaluated through incorporating and averaging several CNN architectures, with a favourable outcome when compared to the ISIC 2018 challenge live leader board
Deep convolutional approach to skin cancer detection and segmentation [11]	InSiNet	Convolutional Neural Networks (CNN)	HAM10000 (Human Against Machine dataset)	InSiNet framework beat prior machine learning approaches in terms of computation time and accuracy, with scores for accuracy of 94.59%, 91.89%, and 90.54% in the relevant ISIC 2018, 2019, and 2020 datasets.
An accurate and noninvasive skin cancer screening based on imaging technique [12]	Keras Sequential API,LeNet,Alexnet, VGG	Convolutional Neural Network (CNN)	HAM10K (Human Against Machine dataset)	When compared to the living state-of-the-art activation function, efficient activation function (AF) addresses the deteriorating gradient problem for skin cancer detection with better accuracy for tailored CNN architecture, with 98.20% accuracy for HAM10K.
Hybrid Deep Learning Approach for Skin Lesion Segmentation and Classification [13]	HR-IQE algorithm, Swarm Intelligence (SI), K-means with Grasshopper Optimization Algorithm (GOA), Speeded-Up Robust Features (SURF)	Convolutional Neural Network (CNN)	ISIC-2017,ISIC-2018, andPH-2 data sets.	Classification accuracy, sensitivity, specificity, F-measure, precision, MCC, dice coefficient, and Jaccard index have been evaluated, with an average of 98.42%, 97.73%, and 0.9704% MCC.
Early and accurate detection of melanoma skin cancer using hybrid level set approach [14]	Averaging, Region of Interest (ROI), Hough Transform (HT), Improved SVM	Convolutional Neural Network (CNN)	Melanoma Skin Cancer Dataset (Sampled Data)	In the article, an improved approach for distinguishing lesions from surrounding tissue is proposed. This is followed by a classifier and the available features, which achieved an accuracy and success rate of 94% and 93%,
Skin cancer detection from dermoscopic images using deep learning and fuzzy k-means clustering [15]	Faster region-based convolutional neural networks (RCNN), fuzzy k-means clustering (FKM)	Convolutional Neural Network (CNN))	ISIC-2016, ISIC-2017, and PH2 datasets	Utilising RCNN and FKM, a fully automated system for segmenting cutaneous melanoma at its initial stages has an average accuracy of 95.40, 93.1, and 95.6%.

Table-1: Comparison of various approaches for Melanoma Skin Cancer Disease

IV. CONCLUSION

In recent years, dermatological issues have become more prevalent than ever as the prevalence of various allergies increases. Since most skin conditions have a tendency to spread from person to person, it is crucial to control them early or stop them from getting severe. In this work, we evaluated various methods for melanoma detection and categorization. Data collection, preprocessing, division, feature extraction, post-handling, and arranging are some of the stages of the melanoma detection process that must be accomplished in order to receive reliable results. According to the research done on all of these methods now in use, neural network-based classification is superior to other methods. But one problem is that training the system for appropriate true detection takes a lot of time. With the construction of a reliable method, true detection grows to a significant level while reducing computing time.

REFERENCES

[1] Banerjee, S., Singh, S. K., Chakraborty, A., Das, A., & Bag, R. (2020). Melanoma Diagnosis Using Deep Learning and Fuzzy Logic. *Diagnostics (Basel, Switzerland)*, *10*(8), 577. https://doi.org/10.3390/diagnostics10080577

[2] M. Julie Therese, A. Devi, G. Kavya (2021) Melanoma Detection on Skin Lesion Images Using K-Means Algorithm and Svm Classifier, Handbook of Deep Learning in Biomedical Engineering and Health Informatics, 1st Edition, Pages 344, Taylor & Francis Group, Apple Academic Press, eBook ISBN9781003144694, https://doi.org/10.1201/9781003144694

[3] KritikaSujay Rao, Pooja Suresh Yelkar, Omkar Narayan Pise, Dr. SwapnaBorde, 2021, Skin Disease Detection using Machine Learning, International Journal of Engineering Research & Technology (IJERT) NTASU – 2020, Volume 09, Issue 03, ISSN: 2278-0181, DOI: 10.17577/IJERTCONV9IS03016

[4] Arjun K P and K. Sampath Kumar, Classification of Skin Melanoma Using Neural Network to Discover an Optimal Solution for Imbalanced Dataset, Tianjin DaxueXuebao (ZiranKexueyuGongchengJishu Ban)/ Journal of Tianjin University Science and Technology ISSN 0493-2137, Vol 54 Issue 07, 2021 DOI 10.17605/OSF.IO/THJE9

[5] Vijayalakshmi M M "Melanoma Skin Cancer Detection using Image Processing and Machine Learning" Published in International Journal of Trend in Scientific Research and Development (ijtsrd), ISSN: 2456-6470, Volume-3 | Issue-4, June 2019, pp.780-784, URL: https://www.ijtsrd.com/papers/ijtsrd23936.pdf

[6] Pallavi, B &Keshvamurthy (2019). A Hybrid Diagnosis System for Malignant Melanoma Detection in Dermoscopic Images. 1471-1476. 10.1109/RTEICT46194.2019.9016745.

[7] Alwakid, G., Gouda, W., Humayun, M., &Sama, N. U. (2022). Melanoma Detection Using Deep Learning-Based Classifications. Healthcare (Basel, Switzerland), 10(12), 2481. https://doi.org/10.3390/healthcare10122481

[8] Reshma G., Al-Atroshi C., Nassa V.K., Geetha B., Sunitha G., Galety M.G., Neelakandan S. (2022) Deep Learning-Based Skin Lesion Diagnosis Model Using Dermoscopic Images. Intell. Autom. Soft Comput. 2022, 31, 621–634. doi: 10.32604/iasc.2022.019117.

[9] Vatekar, Prof &Phapale, Sakshi&Bhor, Akshada& Patel, Chirag &Tiwary, Ayush. (2023). Skin Cancer Prediction using Deep Learning. International Journal of Advanced Research in Science, Communication and Technology. 570-574. 10.48175/IJARSCT-8541.

[10] Aldwgeri, Ather&Abubacker, Nirase. (2019). Ensemble of Deep Convolutional Neural Network for Skin Lesion Classification in Dermoscopy Images. 10.1007/978-3-030-34032-2_20.

[11] Reis, H. C., Turk, V., Khoshelham, K., & Kaya, S. (2022). InSiNet: a deep convolutional approach to skin cancer detection and segmentation. Medical & Biological Engineering & Computing, 1-20. https://doi.org/10.1007/s11517-021-02473-0

[12] Rajput, G., Agrawal, S., Raut, G., &Vishvakarma, S. K. (2022). An accurate and noninvasive skin cancer screening based on imaging technique. International Journal of Imaging Systems and Technology, 32(1), 354-368.

[13] Thapar, P., Rakhra, M., Cazzato, G., & Hossain, M. S. (2022). A Novel Hybrid Deep Learning Approach for Skin Lesion Segmentation and Classification. Journal of healthcare engineering, 2022, 1709842. https://doi.org/10.1155/2022/1709842 (Retraction published J Healthc Eng. 2023 May 24;2023:9832712)

[14] Ragab M, Choudhry H, Al-Rabia MW, Binyamin SS, Aldarmahi AA and Mansour RF (2022) Early and accurate detection of melanoma skin cancer using hybrid level set approach. *Front. Physiol.* 13:965630. doi: 10.3389/fphys.2022.965630

[15] Nawaz, M., Mehmood, Z., Nazir, T., Naqvi, R. A., Rehman, A., Iqbal, M., & Saba, T. (2022). Skin cancer detection from dermoscopic images using deep learning and fuzzy k-means clustering. Microscopy Research and Technique, 85(1), 339– 351.https://doi.org/10.1002/jemt.23908