

Skin Cancer Detection and Classification using Deep learning methods

Anchal Kumari¹ and Dr. Punam Rattan^{2*}

¹Research Scholar, Lovely Professional University, Jalandhar, Punjab India

²Associate Professor, Lovely Professional University, Jalandhar, Punjab India

*Correspondence: Dr. Punam Rattan; punamrattan@gmail.com

ABSTRACT- Skin cancer is a very dangerous disease that needs to be found early, so that it can be treated effectively. In the past few years, classifiers built on convolutional neural networks (CNNs) have become the best way to find melanoma. According to the review, the CNN-based classifier is as accurate as dermatologist in classifying skin cancer images, allowing for faster and more accurate detection. This article examines the most recent studies on Machine learning and deep learning-based melanoma categorization in depth. We provide a comprehensive description of the machine learning and deep learning classifier, including details on the accuracy of these classifiers. The primary objective of this research is to analyze and collect current research trends, issues, and opportunities for melanoma diagnosis, as well as to investigate the current approach for using deep learning to detect and recognize melanoma. The main finding of this review is that the neural network provides high accuracy as comparison to machine learning methods.

Keywords: Skin Lesion, Deep Learning, Ceroscopy, Classification, Neural Network, Melanoma.

ARTICLE INFORMATION

Author(s): Anchal Kumari and Dr. Punam Rattan;

Received: 13/09/2023; **Accepted:** 01/11/2023; **Published:** 30/11/2023

e-ISSN: 2347-470X;

Paper Id: IJEER 1309-08;

Citation: 10.37391/IJEER.110427

Webpage-link:

<https://ijeer.forexjournal.co.in/archive/volume-11/ijeer-110427.html>



Publisher's Note: FOREX Publication stays neutral with regard to Jurisdictional claims in Published maps and institutional affiliations.

1. INTRODUCTION

According to research conducted by the WHO (World Health Organization), cancer is one of the top causes of mortality worldwide. The number of cancer diagnoses expected to double over the next 20 years. Cancer mortality rates can be decrease, if the disease identified and treated in its early phases. Researchers' primary objective is to focus their study efforts on creating early cancer detection methods[1]. The most lethal skin cancer called melanoma. It is seventh on the list of the most common malignancies[2]. There are almost 132,000 new cases found annually. According to American Cancer Society forecasts, 192,310 new instances of melanoma will be detected in the US in 2019 compared to the preceding 30 years. In the early phases of melanoma detection, a small surgical procedure may increase the likelihood of recovery[3]. It enlarges the skin lesion's surface, making the dermatologist's inspection of it easier to see the lesion's structure. However, the results are entirely dependent on the specialist's level of clarity of vision and years of practice, trained healthcare professionals can only properly use this method[4]. These challenges motivates researchers to develop cutting-edge techniques for melanoma imaging and diagnosis[5]. The diagnosis of melanoma cancer is facilitated through the utilization of a Computer-Aided

Diagnosis (CAD) system[6]. The utilization of computer-aided diagnostic (CAD) instruments can serve as a supplementary diagnostic tool for the identification of melanoma cancer. In this study, we cover a variety of CNN-based models and standard datasets for melanoma detection, both published and unpublished. The objective of this work is to present a thorough examination of the existing body of literature relevant to the utilization of deep learning techniques in the context of identifying skin cancer. The present paper provides an overview of the proposed classification and model for melanoma detection by analysing several deep learning techniques. In addition, this review highlights current research directions, unresolved problems, and difficulties in the area of melanoma diagnosis.

There are six sections in this paper. In *section 1*, we give an Introduction and discuss of our objectives. The research methods for literature reviews are presented in *section 2* by outlining the research questions for the study, the scope of the literature survey, the source of knowledge, search procedure, search pattern and classification of different classifier for detection skin diseases. *Section 3*, present discussion about results of the research questions and relevant datasets. In *section 4* lays out the classification methodology used for melanoma detection. Opportunities and difficulties are discussed in *section 5* and the key points of finding result or future work are discuss in *section 6*.

2. RESEARCH FRAMEWORK

This study identified the top deep learning melanoma classifiers, methodologies, and datasets. It helps to find and assess relevant study domain research after review. The categorization of related studies within the study's findings provides empirical support for the outcomes. This study comprises publications sourced from specific research sources

that employ convolutional neural network (CNN) techniques or utilize pre-trained CNN models for the purpose of melanoma detection.

2.1 Review Method

A comprehensive investigation can be defined as a systematic and thorough examination aimed at developing a review procedure. The study strategy is the methodical process of formulating a search strategy to extract relevant data from the data that is accessible. Search parameters, research questions, information sources including conferences, journals and criteria for incorporating and excluding material are all provide in this method for reviewing the literature. A systematic literature review goes through the steps depicted in *figure 1*.

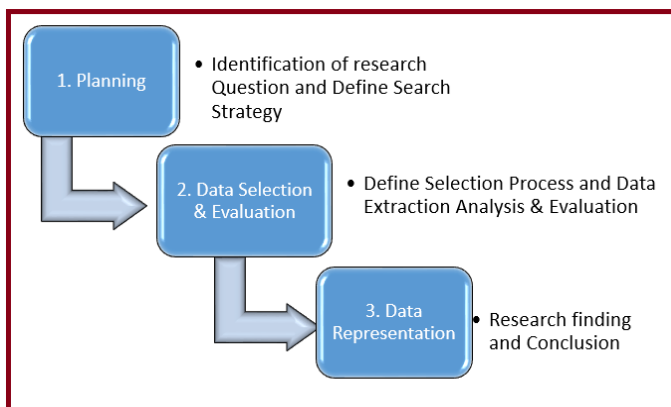


Figure 1: Review Method [14]

2.2 Objectives of the Article

The following are the highlights of this article:

- To recognize the current challenges, opportunities, and trends in melanoma classification and diagnosis studies.
- Examine different methods that currently applied for melanoma classification or detection and give an in-depth

look at the differences and similarities between these techniques' precision and flexibility.

- To develop a framework that focuses upon effective deep neural system methods for cancer diagnosis
- Worked on innovative research into deep learning methods applied for detection or classification of melanoma diagnosis.

2.3 Research Question

A systematic review is required to conduct an in-depth study of the major research issues. Following the formulation of research questions, the analysis step comprises developing search strategies to discover and extract relevant papers. The answers to these requests were located in the published literature, according to the methods provided. The primary goal of this study is to provide a comprehensive overview of the most recent methodologies for melanoma diagnosis using CNN-based models. As can be seen in the following illustration, the research questions that were generated in order to evaluate the importance of the study are provided below *figure 2*.

2.4 Search Strategy Followed

A rigorous and well-planned search is essential to find relevant domain data. This stage involves a thorough search to identify relevant and important facts. We created an automatic search method to exclude target domain data from all sources. We carefully analyzed all pertinent research publications, case studies, American Cancer Society reports, and book reference lists. Skin illness, hazards, causes, and Neural Network detection websites have been thoroughly searched. We searched for relevant data using the following criteria. The search has expanded to include synonyms for different keywords like Cancer, Skin disease, Machine Learning method, CNN, SVM and Skin Lesion etc. Additionally, the logical operators "AND" and "OR" were used between terms during the search.

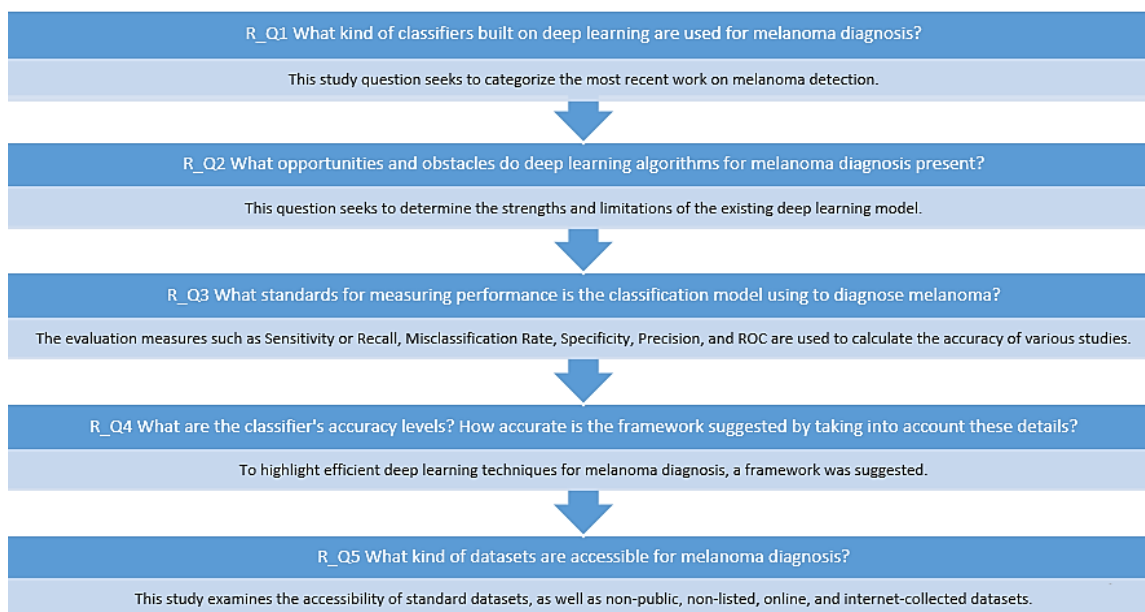


Figure 2: Research Question

2.5 Resources Explored

Firstly, author used reliable search engines like IEEE, Scopus, Springer, and Google Scholar to find information about machine learning methods for diagnosing skin cancer.

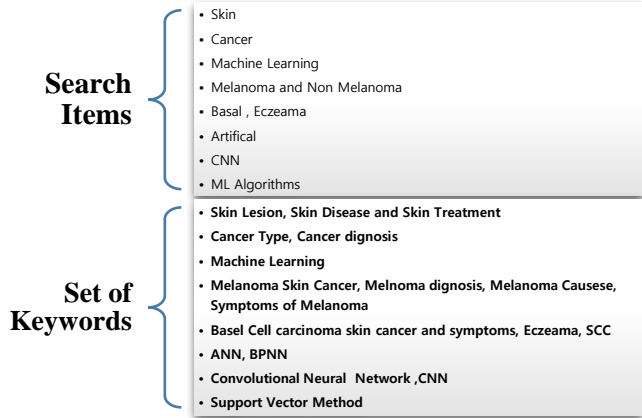


Figure 3: Research Resource

The chosen study articles and conference proceedings looked at more closely according to the assessment standards. In past, most researchers have used a variety of classification methods for detection of skin diseases in automatically, quickly, and accurately way. Authors searched for relevant information using a hand search method from Science Direct, PubMed, and then consulted a list of key words relating to skin lesions. Authors went through the abstracts, and if the abstracts looked promising, the items obtained.

We employed the criteria for high quality literature to selecting paper from past studies. This study did not limit the outlet of publication to a specific country or area. This study illustrates the cause of skin cancer and by applying suitable algorithm. Authors exclude unpublished books and paper. Based on the criteria we selected 60 papers and out of these only 56 papers found to be suitable for the main citation of the study shows in figure 4.

Table 1: Skin Disease Detection Using SVM

Ref.	Skin Disease	Dataset Used by researcher	Work done	Classification Method Used	Outcome
[7]	Melanoma and Seborrheic keratosis	ISIC 2017	Proposed an automatic computerized method with help of pre-trained deep model i.e., AlexNet, VGG16 and ResNet18.	SVM	ROC value for melanoma -83.83% and for seborrheic keratosis- 97.55%
[8]	Melanoma, Eczema, Corn, Psoriasis, Onychosis, Acne	Cairo University Hospital, Beni-Suef University Hospital and various websites	Described the challenges of medical infrastructure and medical facility by proposed a system that used SVM, CNN, and MAA for detection skin disease. This model used only six type skin diseases and with comparing the result from other approaches, it concludes that SVM algorithm gave highly accurate result	SVM	92.1%
[9]	Herpes, Dermatitis, and Psoriasis	NA	Proposed a method for recognition the skin images with Image Color and Texture Feature and it provided the different recognition rate.	SVM	Recognition rate for Herpes-80% Dermatitis – 90 and Psoriasis- 95%

After the reviewed, we classify the paper according to the used techniques and describe the skin disease classes and dataset used for experiment.

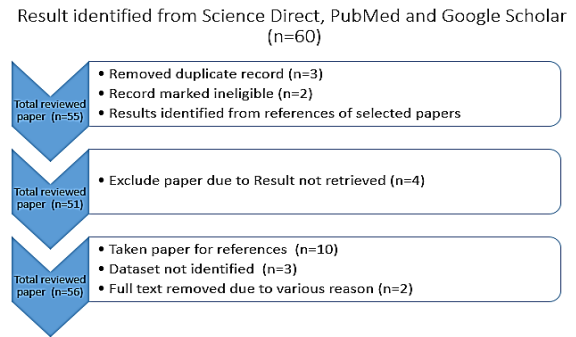


Figure 4: Flow chart of selected paper

The review was further subdivided into different parts according to classification method that is SVM, ANN, CNN and other classifier.

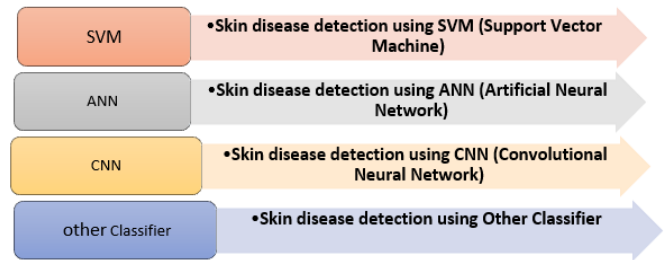


Figure 5: Algorithms used for selected papers

2.5.1 Skin Disease Detection using Support Vector Machine (SVM)

The following table highlights the papers reviewed which used SVM as major algorithm.

[10]	Melanoma	NA	In this paper various image feature like area, perimeter and mean (R), mean (G), mean (B) and texture features extract that used to detect spot of cancer and guides for the direction of spread of the cancer with help of SVM classification.	SVM	Good accuracy
[11]	Skin cancer images	ISIC-2016	This paper proposed a system that apply SVM for cancerous and non-cancerous cell in the input image. GLCM was use for extract feature from input image and SVM for classification.	SVM	95%
[12]	Melanoma	Kwait Incp ISIC 2016 and Skin Vision BV	Proposed a method for classify the dermoscopy image whether it is melanoma or benign. From the experiment with the SVM classification, it shows the 92.1% accuracy for classification of melanoma skin image.	SVM	92.10%
[13]	Eczema, Fungal infection, Urticarial.	Capture image through smart-phone camera	The disease predicted by the system for a new image of a skin disease collected by the user using an Android application. This study emphasized the need of dermatologists increasing diagnostic time and intervention accuracy.	SVM, C4.5	Good accuracy
[14]	3 different skin disease	From online	Developed a simple system for detection of skin disease in Saudi Arabia. SVM classifier performs classification with 100-skin image dataset from numerous dermatological patients from web application and internet	SVM	100%
[15]	Melanoma	From skin disease-specific websites	Developed a simple system for detection of skin disease in Saudi Arabia. SVM classifier performs classification with 100-skin image dataset from numerous dermatological patients from web application and internet.	SVM, BPAN and CNN.	SVM has provide accurate result than other
[16]	Bacterial infections, fungal infections, eczema and Scabies	NA	This paper Proposed a model with SVM & ANN. This model implemented using MATLAB14 with neural network toolbox with both classification model calculates the confusion matrix for accuracy.	SVM	95.39%
[17]	Melanoma	Digital dermoscopy images and collected from various medical sites	This research described a CAD system that employed the SVM model to detect Melanoma skin cancer. HOG feature analysis for Melanoma skin cancer diagnosis.	SVM	97.32%.
[18]	Melanoma	https://www.kaggle.com/drscarlat/melanoma	Objective of this paper to classify the melanoma & non-melanoma by applied SVM & image processing technique. From the experiment, it shows that SVM gives the better result.	SVM	Good accuracy
[19]	Melanoma, Basal Cell Carcinoma, Eczema, and Impetigo.	Online repositories Dermis dataset and Dermatology Information System.	The improved automated skin diagnostic model uses deep learning CNN for feature extraction and SVM for classification and performed well in sensitivity, specificity, and accuracy.	SVM	94%

2.5.2. Skin Disease Detection Using Artificial Neural Network (ANN)

The following table highlights the papers reviewed which used ANN as major algorithm.

Table 2 Skin Disease detection using ANN

Ref.	Skin Disease Name	Dataset used by researcher	Work done	Classification method used	Outcome
[20]	Melanoma	NA	Described the detection of early skin cancer but only an expert dermatologist can classify which was benign or malignant.	Artificial Neural Network (ANN) and MATLAB	84%
[21]	Skin Disease Analysis of normal and abnormal skin	Dermatlas	The finding of the study clearly revealed that with the help of algorithm and root method on data images the error rate is 0.0099627170 and detection rate is 96.50.	MLP algorithm (feedforward neural network)	96.70%
[22]	Foot ulcers, Vitiligo, Tinea Corporis, Pityriasis Rosea, Leprosy, Scabies, and Psoriatic arthritis	Dermatology Department, Mitford Hospital, Sir Salimullah Medical College, Dhaka, Bangladesh.	The experiment used 775 color skin images from 128 dermatological disease patients and gave high accuracy, demonstrating that supervised systems operate better than semi-supervised and unsupervised systems.	Feed-Forward back-propagation neural network with tenfold cross validation process.	90%
[23]	Eczema Disease	Dermnetz	This paper introduced Eczema disease detection with cloud computing model. For diagnoses of ED used BPNN (backpropagation neural network) in cloud computing.	BPNN, ANN	Good accuracy
[24]	Skin Diseases Diagnosis	Machine Learning Repository Dermatology Data Set	This paper presented a comprehensive examination of the artificial neural network (ANN) algorithm employed in the medical field for diagnosing skin diseases. The study also utilizes MATLAB, together with the Neural Network toolbox, to model ANN for medical decision-making purposes.	ANN	93.70%
[25]	Pediculosis capitis, Pityriasis versicolor, Seborrheic Dermatitis, Vitiligo, Warts, Folliculitis, Leprosy, Lichen Planus, Warts, Herpes Zoster	Department of Skin and G. S. M. C. KEM Hospital, Parel Mumbai	A novel multiclass system has been developed to diagnose skin illnesses by detecting the condition based on user input symptoms. The classifiers employed in the classification task were evaluated and it was determined that Artificial Neural Networks (ANN) and Random Forest (RF) yielded superior outcomes.	ANN & RF	90%

2.5.3 Skin Disease Detection Using Convolutional Neural Network (CNN)

The following table highlights the papers reviewed which used CNN as major algorithm.

Table 1: Skin Disease detection using CNN

Ref.	Skin Disease Name	Dataset used by Researcher	Work Done	Classification method used	Outcome
[26]	Melanoma	ISIC	A methodology presented for the categorization of skin cancer images into malignant and benign categories using color and texture-based feature extraction approaches. From the comparing both techniques SVM and CNN to diagnoses the skin cancer image, it manifests that CNN gives better accuracy then SVM	SVM and CNN	CNN gives better accuracy then Support Vector Machine
[27]	Melanoma	ISIC 2017	Proposed an automated system with help of CNN model i.e., Inception- V3	CNN (Inception – V3)	82.50%

			From the experiment, system achieved high accuracy i.e., 82.5% & 81.4% on 4000 th iteration and the AUC score of this system 65.8% achieved with validation set in ISBI Challenge.		
[28]	Melanoma, Impetigo and Eczema	From surveys and websites.	This study introduced a diagnostic system for three types of skin diseases using image processing and deep learning methodologies. Due to its mobile-based nature, this technology has the potential to use in even the most distant places.	SVM & CNN	CNN gives accurate and efficient result as compared to SVM Classifier
[29]	Atopic dermatitis, Acne vulgarizes & scabies.	Four Sunyani Municipality, Ghana, medical centers	Provided a web-based system for skin disease detection i.e., Medilab-plus with CNN classifier with TensorFlow framework for three different diseases i.e., atopic dermatitis, Acne vulgarizes & scabies.	CNN classifier	Dermatitis- 88%, Acne- 85% vulgaris and scabies - 84.7%
[30]	Benign Nevus and Melanoma	International Skin Imaging Collaboration (ISIC) archive	For experiment, it takes input image from ISIC data i.e., 50% image of melanomas & 50% image of benign lesions. After that enhance the image with pre-processing procedures for classification CNN used with 14 layers and achieve good accuracy	CNN classifier	97.70%
[31]	Melanoma	ISIC	A comparative analysis of the use of Convolutional Neural Networks (CNN) to analyze melanoma images presented in this article. The ResNet50 convolutional neural network (CNN) architecture used in this research.	ResNet50	CNN achieves high sensitivity- 82.3 and specificity-77.9%.
[32]	Lichen, Acne, planus and sjs ten	NA	This research explores the use of a machine-learning algorithm on three distinct types of skin diseases, namely Acne, Lichen planus, and SJS-TEN. 300 skin images were use in the development and validation of the proposed framework.	logistic regression kernel SVM, Naive bayes, RF and CNN	CNN provide best result with accuracy 96% and error rate 0.04%
[33]	Benign or Malignant [BCC: basal cell carcinoma; MM: malignant melanoma; SK: seborrheic keratosis; H/H: hematoma/hemangioma; SL: senile lentigo]	Dermatologic Oncology Department, National Cancer Center Hospital Japan	In the conducted experiment, a group of 20 dermatologists examined and their accuracy has compared with the performance of the Faster R-CNN (FRCNN) model. The results indicated that the accuracy of the Faster R-CNN model was superior to that of the dermatologist.	CNN	For six-class FRCNN, 86.2%- s and TRNs- 79.5% and 75.1%, respectively; For two-class accuracy- 91.5%, sensitivity-83.3%, and specificity-94.5%.
[34]	6 diseases (Acne, Actinic, psoriasis, Tina ringworm, eczema and seborrhea)	Dermoscopic images were collected from Internet	This paper develops android application that help to patients for diagnosis the diseases.	CNN (MobileNet Model)	81%
[35]	Nevus and Melanoma	ISIC 2017 and PH2	Different approaches applied to selected image data augmentation during training image test time augmentation during inference stage with brittleness on artificial & natural CNN architecture decrease the brittleness of image that vary the degree of image with respect to maintain the performance. The discover refinement was greater for the artificial than natural set.	ResNet 50, Densenet121, VGG16	Good Accuracy

[36]	Dermatofibroma, Basal cell carcinoma, actinic keratosis, vascular lesions, and melanocytic nevi	HAM10000 dataset	Developed a Deep Learning model for identification the health and unhealthy skin	CNN	93%
[37]	skin lesion	Dermoscopic images were collected from Internet	Main objective of this paper to recognition the different skin lesion in timely detect to help cure the patients due to diabetes from the skin cancer	Deep CNN and SVM	CNN+SVM-91%
[38]	Benign and Malignant	ISIC	This paper proposed a model with CNN for classification of skin lesion for benign and malignant from experiment, it take data from ISIC archive.	BP-CNN, BN-CNN	CNN provides good accuracy
[39]	Glaucoma diagnosis, Alzheimer's disease, bacterial sepsis diagnosis	NA	From the survey on ML algorithms, it stated that ANN, SVM algorithm and deep learning model like CNN used for high accurate result and performance.	ANN, SVM and CNN algorithm	CNN has provided good evaluation performance and accurate result
[40]	Benign Nevus, Melanoma or Seborrheic Keratosis,	ISIC 2017, PH2	From comparing the result of different dataset, it showed that proposed model CSARM-CNN has provide higher accuracy result.	CSARM-CNN	Accuracy-95.0% Sensitivity-80.22%, Specificity-99.40%
[41]	Skin images	NA	This system used ResNet152v2 method for feature extraction and SoftMax image classifier for diagnosis. CNN method used for classification of images and provide better accuracy that another classifier.	ResNet152v2	Good Accuracy

2.5.4 Skin Disease Detection using Hybrid Classifier

The following table highlights the papers reviewed which used hybrid classifiers as major algorithm.

Table 2: Skin disease detection using Hybrid Classifier

Ref.	Skin Disease Name	Dataset used By Researcher	Word Done	Classification method used	Outcome
[42]	Shingles, Squamous cell Melanoma, Bullae, Seborrheic keratosis,	ISIC	After comparing SVM, K-NN and fusion based SVM, k-NN classifier, it exhibits that Fusion based SVM, k-NN classifier gave 61% accurate result	SVM + k-NN classifiers	F-measures for SVM and k-NN models of 46.71% and 34%, respectively, and 61%-SVM and k-NN fusion.
[43]	Melanoma	International Skin Imaging Collaboration (ISIC) archive	From the testing the different classification, it provided the different score value for classification accuracy, sensitivity & specificity i.e. (0.826, 0.533, 0.898, 0.780) with better result than other approaches	AlexNet combined with SVM	Accuracy-0.826, Sensitivity-0.533, Specificity- 0.898 and AOC-0.780
[44]	Bacterium, fungi, and virus	NA	A mobile application developed for the Android platform, employing the nearest neighbor method for classification and leveraging the HSV color space as a means of image processing.	Nearest Neighbor using HSV	80%
[45]	Psoriasis, lichen planus, rosea, rubra, and seborrheic dermatitis	UCI machine repository	A study that focused on five distinct data mining techniques—namely as DT, RF, GBDT, CART, SVM carried out. By using all five approaches together, we were able to achieve the greatest accuracy of 98.64% and significantly minimize the error rate.	DT, RF, GBDT, CART, SVM	98.64%

[46]	Melanoma	Wollongong, New South Wales, Australia location of the Southern Pathology Laboratory.	An automated method utilizing a hybrid approach of Particle Swarm Optimization and SVM (PSO-SVM) was developed.	Particle Swarm optimization & SVM	WPT-SFS- SVM - 77.4 % & WPT-PSO-SVM Accuracy - 87.1%, Sensitivity- 94.1% & Specificity- 80.2%.
[47]	Melanoma	Dermoscopic images were collected from Internet	For feature, extracting as color shape and texture calculate by different matrix MNN and BP used for training the image of the data from the experiment it showed the 89% accuracy for detection the Melanoma or non-Melanoma skin disease.	Matrix MNN and BpNN	80%
[48]	Melanoma	From Clinic images	An artificial intelligence algorithm has developed to identify melanoma in pigmented skin lesions, both those that were biopsied and those that were not.	Artificial Intelligence Algorithm	AUROC 95.8% and 100% sensitivity with specificity of 64.8%,
[49]	Vascular tumors, Actinic Keratosis, Benign keratosis, basal cell cancer, melanocytic nevi, dermatofibroma	Medical University of Vienna's ViDIR Group, Dermatology Department (HAM10000 dataset)	By applying the fine-tuning and ensemble learning model, it provided accurate result for classification of skin lesion	Fine-tuning and ensemble learning model	Good Accuracy with Fine tuning method
[50]	Melanoma	HAM10000 dataset	With the help of the Discrete Cosine transform and Discrete Wavelet Transform, different skin disease and Classification model for detection skin cancer classified.	Ensemble learning methods	85%
[51]	Melanoma	ISIC-2016	This study proposes a segmentation methodology using a CNN-based U-net architecture, including local binary pattern, Edge Histogram, Histogram of Oriented Gradients (HOG), and Gabor method	CNN	85.19%

2.5.5 Comparative review on parameters used in research

The following table highlights the comparative study of papers

Table 3: Comparative review on parameters used in research

Ref.	Techniques Used	Accuracy	Sensitivity	Specificity	Area Under Curve	Precision	F1 Score
[9]	Image Color and Texture Features	✓	✓	✓	✗	✗	✗
[31]	Deep neural networks	✓	✓	✓	✗	✗	✗
[32]	Machine Learning Algorithms	✓	✗	✗	✗	✗	✗
[33]	Deep Learning	✓	✓	✓	✗	✗	✗
[35]	CNN	✓	✗	✗	✗	✗	✗
[40]	CNN	✓	✓	✓	✗	✗	✗
[43]	Combining Deep Learning	✓	✓	✓	✗	✗	✗

[44]	Data Mining	✓	✓	✓	✗	✗	✗
[45]	Ensemble Data Mining Techniques	✓	✗	✗	✗	✗	✗
[46]	PSO-SVM hybrid system	✓	✓	✓	✗	✗	✗
[48]	Artificial Intelligence Algorithm	✓	✓	✓	✓	✗	✗
[49]	DCNN	✓	✗	✗	✗	✗	✗
[52]	Convolutional Neural Network	✓	✗	✗	✗	✗	✗
[53]	VGGNet model	✓	✗	✓	✗	✓	✗
[54]	XAI-based skin lesion classification	✓	✗	✗	✗	✗	✗
[55]	Ensemble- based Genetic Algorithm	✓	✗	✗	✗	✗	✗
[56]	Deep learning technique	✓	✗	✗	✗	✓	✓
[57]	VGG16 and XGBoost	✓	✗	✗	✗	✗	✗
[58]	FrCN-DGCA	✓	✗	✗	✗	✓	✗

3. DISCUSSIONS

3.1 Search Results

The findings in the context of the questions of the systematic research are discuss in this section. The distribution of 56 selected papers shown in figure 6, along with the number of articles published by each publishing source and a graphic representation of all 56 finalized review papers with various publication sources. At the conference, about 60% of the chosen papers presented. Whereas each given in the 5% symposium and book chapter, and 30% were published in journals show in figure 6.

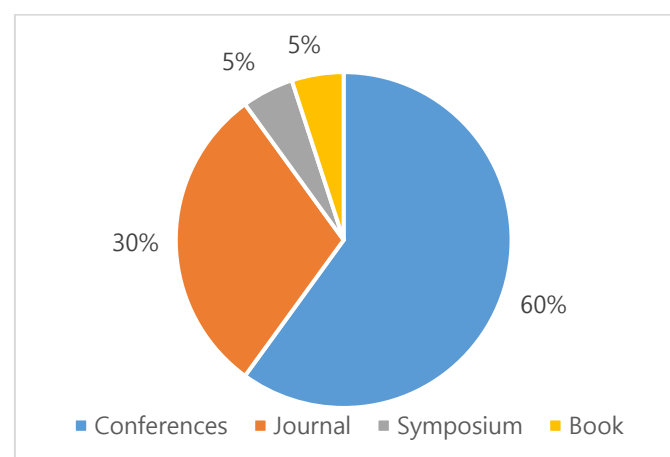


Figure 6: Detail of Specified Resources [61] [55]

Additionally, Pie-Chart diagrams have been used to show the distribution of all sources, including IEEE, ACM, Springer, Science Direct, Wiley, and Medline, as well as the total specified papers from each source.

3.2 Discussion about Research Question

The early and accurate identification of this condition is still crucial. We have looked over the 56 papers that has finalized in light of our study questions. After carefully examining the chosen papers, we select the supporting evidence for analysis from this extensive research area. To promote awareness of how technology detect skin melanoma. Figure 7 shows less skin cancer detection research in 2015 to mid-2023. Uses of advanced technology to detect cancer and non-cancer classification of skin was increase from 2019 to 2023. The following important review questions were explored to get more depth on skin diseases.

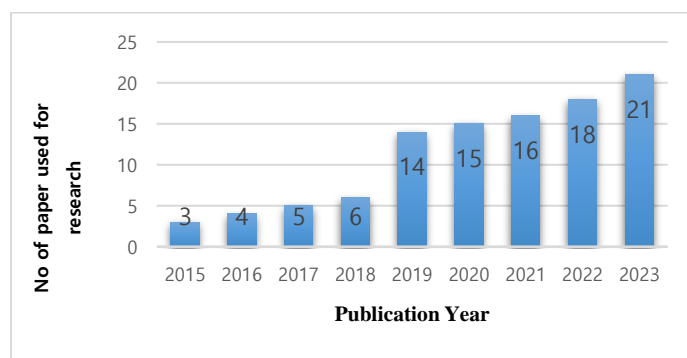


Figure 7: The total number of papers that were utilized in the process model in order to carry out qualitative analysis [67]

A. Which kind classifier based on deep learning used for melanoma diagnosis?

Melanoma is one of the forms of cancer that diagnosed most frequently. Deep learning used to diagnose melanoma in a lot of recent, in-depth research, new methods, and algorithms.

Table 4: Details of Pre-Trained Models

Ref.	Skin Disease Name	Techniques Used	Classification method used	Accuracy
[73]	Melanoma	Deep CNN	Deep CNN	97.3%
[31]	Melanoma	Deep Learning	CNN (Inception –V3)	82.50%
[36]	Melanoma	Deep neural networks	ResNet50, CNN	CNN achieves high sensitivity- 82.3 and specificity-77.9%.
[40]	Nevus and Melanoma	CNN	ResNet50, Densenet121, VGG16	Good Accuracy
[41]	Melanoma	Convolutional Neural Network	CNN with LeNet architecture	Good Accuracy
[48]	Benign Nevus, Melanoma or Seborrheic Keratosis,	CNN	CSARM-CNN	sensitivity-80.22%, specificity-99.40% and accuracy-95.0%
[56]	Melanoma	PSO-SVM hybrid system	Particle Swarm optimization & SVM (PSO-SVM).	WPT-SFS- SVM - 77.4 % & WPT-PSO-SVM accuracy - 87.1%, sensitivity- 94.1% & specificity- 80.2%.
[59]	Melanocytic nevi, Melanoma, Benign keratosis	DCNN	Inceptionv3 and DenseNet-201	Good Accuracy with Fine tuning method
[67]	Melanoma	DCNN	DenseNet201, Res50V2, ResNet152V2, Xception, VGG16, VGG19, GoogleNet	GoogleNet had the highest accuracy

B. What standards for measuring performance is the classification model using to diagnose melanoma?

The correctness of a number of research evaluated by employing a variety of assessment measures, such as specificity, sensitivity, accuracy, precision, and the Area Under the Curve (AUC). The accuracy of every classifier is determined based on how well these requirements are meet. A summary of performance measures shown in below table:

Table 5: Performance Matrix

Ref.	Evaluation Matrix	Classification method used	Outcome
[19]	Accuracy	SVM, MATLAB 9.0	94%
[27]	Accuracy	CNN (Inception –V3)	82.50%
[29]	Accuracy	CNN classifier with TensorFlow	88%-dermatitis, 85%- arcane vulgaris and 84.7%-scabies
[30]	Accuracy	CNN	97.70%
[31]	Accuracy, Sensitivity, Specificity	ResNet50 CNN	CNN achieves high sensitivity- 82.3 and specificity- 77.9%.
[34]	Accuracy	CNN (MobileNet Model)	81%
[36]	Accuracy	CNN with Keras application API.	93%
[40]	Accuracy, Sensitivity, Specificity	CSARM-CNN	Accuracy- 95.0%, Sensitivity- 80.22% and

			Specificity- 99.40%
[43]	Accuracy, Sensitivity, Specificity	AlexNet combined with SVM	Accuracy- 0.826, Sensitivity- 0.533, Specificity- 0.898 and AOC-0.780
[46]	Accuracy, Sensitivity, Specificity	Particle Swarm optimization & SVM (PSO-SVM).	WPT-SFS- SVM - 77.4 % & WPT-PSO-SVM accuracy - 87.1%, sensitivity- 94.1% & specificity- 80.2%.
[47]	Accuracy	Matrix MNN and BpNN	80%
[48]	AUROC, Accuracy, Sensitivity, Specificity	Artificial Intelligence Algorithm	AUROC 95.8% and 100% sensitivity with specificity of 64.8%,

C. What are the classifier's accuracy levels? How accurate the framework suggested by taking into account these details?

The current methods for classifying and detecting melanomas were thoroughly analysed in this study. A melanoma

categorization applied to summarize the results of this investigation.

D. What kind of datasets are accessible for melanoma diagnosis?

For the identification of skin lesions, various data sets were accessible. Some of them were accessible to everyone, while others were not. A summary of the standard datasets shown in the following *table 8*. The datasets below chosen as a standard because they were used so frequently in research to find melanoma.

Table 6: Details of Dataset used by researchers

Ref.	Datasets Used	Outcome
[8]	Cairo University Hospital, Beni-Suef University Hospital, and internet pages	92.1% (CNN)
[12]	Kwait Incp, "International Skin Cancer Collaboration: Melanoma (ISIC 2016) and Skin Vision BV	92.1% (SVM)
[16]	Skin and V.D. Department, Shrikrishna Hospital, Karamsad, Gujarat, India.	95.39 % (SVM)
[18]	https://www.kaggle.com/drscarlat/melanoma	Good accuracy (SVM)
[22]	Sir Salimullah Medical College and Mitford Hospital.	90% (ANN)
[24]	Machine Learning Repository Dermatology Data Set	93.70% (ANN)
[25]	Department of Skin in KEM Hospital Mumbai	90% (ANN & RF)
[28], [48]	From surveys and websites and From Clinic images	CNN provided accurate and efficient result as compared to SVM Classifier[28] , AUROC 95.8% and 100% sensitivity with specificity of 64.8%(ANN) [48]
[29]	Four Sunyani Municipality, Ghana, medical centers	88%-dermatitis, 85% - arcane vulgaris and 84.7%-scabies (CNN)
[34], [37], [47]	Dermoscopic images collected from Internet	81%(CNN) [34], CNN+SVM-91%[37], 80%(BpNN) [47]
[45], [46]	UCI machine repository and Southern Pathology Laboratory in Wollongong NSW, Australia.	98.64% (SVM) [45] and WPT-SFS- SVM - 77.4 % & WPT-PSO-SVM accuracy - 87.1%, sensitivity- 94.1% & specificity- 80.2%.(PSO-SVM) [46]

[56]	Jimma's Dr. Gerbi medium clinic and Dessie's Borumeda General Hospital	Kappa = 0.976, Accuracy = 97.50%, Precision = 97.50%, Recall = 97.50%, and F1 = 97.50%
------	--	--

4. PROPOSED FRAMEWORK FOR MELANOMA DETECTION

In this analysis, the majority of the findings focused on deep learning for the binary identification of sickness. The intended framework originally classified the skin lesion as either benign or malignant after performing two operations on it. There are four main kinds of melanoma: letigo maligna, Acrel lentiginous, Noda melanoma, and superficial spreading. All of these kinds come in a variety of sizes, colours, shapes, and locations. Lentigo maligna and Acral lentiginous both have irregular shapes and fluctuate in size and hue. The outcomes of this study have been summarized in below *figure 8* by creating a framework for melanoma detection using deep learning.

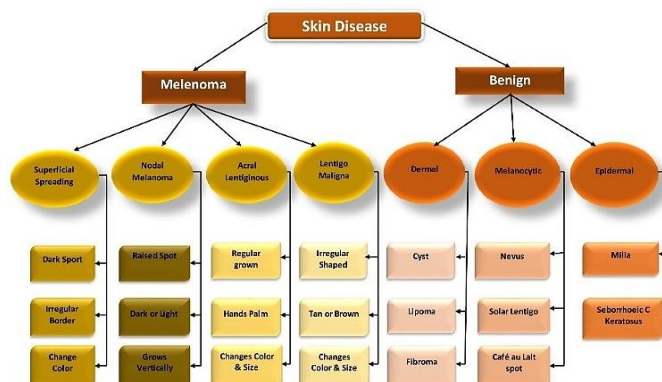


Figure 8: Taxonomy of Melanoma [57]

There are different stages for detection of skin lesion as shown in *figure 9*. In first stage, researchers collect dataset from different primary and secondary resources. There are different online dataset libraries such as PH2, HAM1000, ISIC archive, Dermnet, DermIS etc. In stage 2, Researchers perform different methods for pre-processing the image.

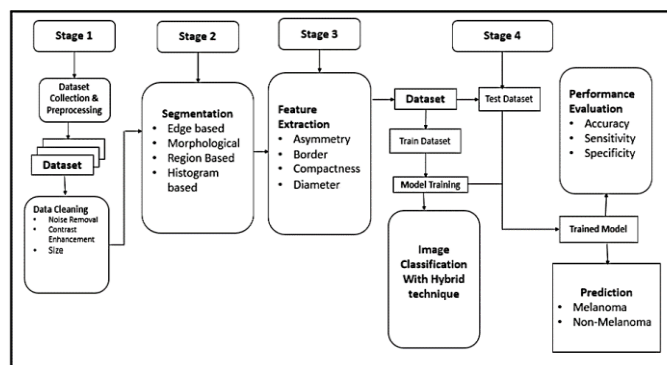


Figure 9: Stages for detection of Skin Lesion

4.1 Pre-processing Step (Stage 1)

The goal of the first step of the suggested method is to make the images better. Every picture is in RGB format. Before segmentation, all pictures should be the same size and have no noise. This will help get better segmentation results, which is the major goal of our technique's pre-processing step.

4.2 Segmentation (Stage 2)

The image containing the noise and other artifacts affect the performance during the segmentation process. The term "segmentation" means operation of dividing a digital image into smaller parts, or "extraction of the area of interest." [61]. Labeled each pixel in an image such that adjacent pixels have the same color, brightness, contrast, and texture values. The goal of segmentation is to change the representation of an image in to a more meaningful representation. Meaningful representation to locate objects and boundaries. Image segmentation has applications in content-based image retrieval, object detection, video surveillance, machine vision, and medical imaging. The segmentation process is enhanced by [62] using the property of similarity in the spitted region or groups. The important information and features extracted from the input after segmentation. The objective and purpose of segmentation include the extraction of the damaged region, namely the lesion area, from the backdrop, which consists of normal healthy skin. The process of identifying multiple clinical characteristics, both locally and worldwide, in the context of melanoma diagnosis may be laborious. The boundary of the segmented melanoma provides useful information. Accurate diagnosis can be done by correct lesion classification. The efficient melanoma segmentation of leads to desired feature extraction and also improves the performance of the lesion. The operational categorization of segmentation algorithms may broadly group into three distinct types: manual segmentation, semi-automatic segmentation, and completely automated segmentation.

4.3 Feature Extraction and Classification (Stage 3 and Stage 4)

The process of separating the features from the background of the segmented images is termed as feature extraction. It is essential to extract and calculate the features to categorize the classes from one another. The pattern classification plays a significant role in classifying and identifying the features that was difficult to recognize by the dermatologist. Colour feature is a major example for the identification and detection of melanoma. It helps to differentiate the melanoma from other skin diseases. The goal of melanoma classification is to categorize the melanoma images in to different categories that help the doctors to diagnose the disease or further research. The traditional medical image classification includes two steps. They are (i), extracting the effective features from the image and (ii), building models using the features that classify the image dataset. Classification employs two processing phases namely training and testing. In the training phase, image features are isolated and a unique description of each classification category (training class) created. The labelling of the images in to one of the predefined categories is termed as image classification. The database in the classification system

compares the identified object with the predefined patterns to classify in to suitable class[63].The classification is the final phase that categorizes in to benign or melanoma image. The features are broadly classified in to three types namely, low level features, mid-level features and high-level features. The extraction of feature reduces the time and storage space. Following segmentation and feature extraction, classifiers use the hybrid feature vector to detect melanoma and nevus. We train and evaluate many categorization algorithms at default parameters to obtain high accuracy. There are different classification methods such as SVM, K-nearest neighbor, Decision Tree, CNN, Naive Bayesian etc., According to the data presented in *figure 10*, different diagnostic methods are responsible for identifying 36% of cases of melanoma and either 13% or 14% of cases of dermatitis, herpes, psoriasis, and urticarial. Diseases related to fungal infection, impetigo, foot ulcer, onychosis, acne, corn, pityriasis rosea scabie, tinea corporis, and scabies are regularly diagnosed at a rate of 7%, 5%, 4%, 5%, 7%, and 11%, respectively. Researchers can have a better sense of how to enhance their work in this field by referring to this pie chart.

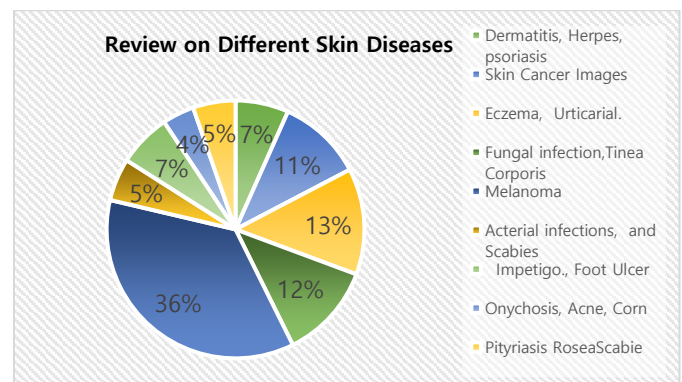


Figure 10: Different Skin Diseases

4.5 Performance Matrix

The parameters of accuracy, precision, sensitivity, specificity, and score for each given response were analyzed in order to assess the classifiers' ability to generalize. True positive (TP) refers to instances where malignant examples have been accurately categorized as malignant. True negative (TN) refers to instances where benign examples have been properly identified as benign. However, false positive (FP) and false negative (FN) refer to instances in which malignant samples are mistakenly classified as benign and benign ones as malignant, respectively. The concepts below are included in the confusion matrix, which is shown as *table 9*.

5. CHALLENGES AND OPPORTUNITIES

Deep learning techniques present both many possibilities and challenges for the detection of melanoma. The issues that noted in the literature are discuss in this section.

5.1 Variation in Datasets

There are not many images in the standard datasets that can used for training and testing, and it found that there are not many pictures in the benchmark datasets that can be used for both

training and testing. ISIC declares an annual challenge to handle the problem identified in 201 in order to resolve it. Additionally, some researchers [18],[10], [30], [31], [35], [43], [36], [52] and [61] combined the various datasets to create a single, sizable image dataset, and then they validated the techniques they had suggested.

5.2 Lesion Size

It has also mentioned that the extent of the lesion is crucial. Lesions under six mm are difficult to identify as melanoma and have a significantly reduced accuracy of detection; lesions over 6 mm considered as melanoma.

5.3 Available Classifications about Melanoma

Models that have trained and handcrafted method-based deep learning have both demonstrated promising outcomes for classification of melanoma with better precision value and accuracy values, according to the literature.

5.4 Effectiveness of the Deep Learning Approach

Following an evaluation of the chosen studies, it found that deep learning techniques work best when 70% of the images carried out for training and 30% for testing.

6. CONCLUSION

The most recent developments in melanoma detection studies have covered in this paper. This study also examined deep learning-based melanomas detection methods. The study discovered following points.

- Neural networks in AI algorithms extensively studied for diagnosing skin lesions and Melanoma detection in imaging applications.
- New databases and obstacles in skin lesion classification are always emerging. The best results were obtained by integrating the decisions and functions of many Neural Networks.
- The increased interest in neural networks for Melanoma detection indicates a desire to apply AI to medical concerns and understand their effectiveness.
- System performance should increase because of the evolution of neural networks, which necessitates updated, adaptable, and integrated networks.

7. FUTURE WORK

In future, these technologies could use to identify Melanoma under the nails and palm, which is harder to diagnose. If the Melanoma affected the nail, then the network training should include the nail. To reduce the probability of overfitting, increase the dataset and optimize the hyper-parameter. To improve outcomes, additional factors like age, gender, and race must be included. The task of raising the accuracy rate still exists, though while increasing the methods' specificity and overall accuracy, the objective must be to achieve the maximum sensitivity.

REFERENCES

- [1] V. Srividhya, R. S. Ponmagal, L. Madheshwaran, V. Srividhya, R. S. Ponmagal, and L. Madheshwaran, "ScienceDirect Vision based Detection and Categorization of Skin lesions using Vision based Detection and

Categorization of Skin lesions using Deep Learning Neural Networks Deep Learning Neural networks," vol. 00, no. 2019, 2020, doi: 10.1016/j.procs.2020.04.185.

- [2] R. Patil and S. Bellary, "Machine learning approach in melanoma cancer stage detection," J. King Saud Univ. - Comput. Inf. Sci., vol. 34, no. 6, pp. 3285–3293, 2022, doi: 10.1016/j.jksuci.2020.09.002.
- [3] A. A. Adegun and S. Viriri, "Deep Learning-Based System for Automatic Melanoma Detection," IEEE Access, vol. 8, pp. 7160–7172, 2020, doi: 10.1109/ACCESS.2019.2962812.
- [4] A. K. Nambisan et al., "Learning-Based Segmentation of Irregular Networks," 2023.
- [5] T. Mazhar et al., "The Role of Machine Learning and Deep Learning Approaches for the Detection of Skin Cancer," Healthc., vol. 11, no. 3, 2023, doi: 10.3390/healthcare11030415.
- [6] M. Fraiwan and E. Faouri, "On the Automatic Detection and Classification of Skin Cancer Using Deep Transfer Learning," Sensors, vol. 22, no. 13, 2022, doi: 10.3390/s22134963.
- [7] A. Mahbod, G. Schaefer, C. Wang, R. Ecker, and I. Elling, "Skin Lesion Classification Using Hybrid Deep Neural Networks," ICASSP, IEEE Int. Conf. Acoust. Speech Signal Process. - Proc., vol. 2019-May, pp. 1229–1233, 2019, doi: 10.1109/ICASSP.2019.8683352.
- [8] A. A. Elngar, R. Kumar, A. Hayat, and P. Churi, "Intelligent System for Skin Disease Prediction using Machine Learning Intelligent System for Skin Disease Prediction using Machine Learning," 2021, doi: 10.1088/1742-6596/1998/1/012037.
- [9] L. Wei, Q. Gan, and T. Ji, "Skin Disease Recognition Method Based on Image Color and Texture Features," vol. 2018, 2018.
- [10] M. S. Poornima and K. Shailaja, "Detection of Skin Cancer Using SVM," 2017.
- [11] I. Journal, "Skin Cancer Detection Using Image Processing".
- [12] H. Alquran et al., "The melanoma skin cancer detection and classification using support vector machine," 2017 IEEE Jordan Conf. Appl. Electr. Eng. Comput. Technol. AEECT 2017, vol. 2018-Janua, no. October, pp. 1–5, 2017, doi: 10.1109/AEECT.2017.8257738.
- [13] R. S. Gound and J. B. Gaikwad, "Skin Disease Diagnosis System using Image Processing and Data Mining," vol. 179, no. 16, pp. 38–40, 2018.
- [14] N. Soliman and A. Alenezi, "ScienceDirect a Method of Skin Disease Detection Using Image Processing and Machine Learning a Method Of Skin Disease Detection Using Image Processing And Machine Learning," Procedia Comput. Sci., vol. 163, pp. 85–92, 2019, doi: 10.1016/j.procs.2019.12.090.
- [15] M. M. Vijayalakshmi, "Melanoma Skin Cancer Detection using Image Processing and Machine Learning".
- [16] K. S. Parikh and T. P. Shah, "Support Vector Machine – a Large Margin Classifier to Diagnose Skin Illnesses," vol. 23, pp. 369–375, 2016, doi: 10.1016/j.procy.2016.03.039.
- [17] S. Bakheet, "An SVM framework for malignant melanoma detection based on optimized HOG features," Computation, vol. 5, no. 1, pp. 1–13, 2017, doi: 10.3390/computation5010004.
- [18] N. V. Kumar, P. V. Kumar, K. Pramodh, and Y. Karuna, "Classification of Skin diseases using Image processing and SVM," Proc. - Int. Conf. Vis. Towar. Emerg. Trends Commun. Networking, ViTECoN 2019, no. March, pp. 1–5, 2019, doi: 10.1109/ViTECoN.2019.8899449.
- [19] D. A. Shoieb, S. M. Youssef, and W. M. Aly, "Computer-Aided Model for Skin Diagnosis Using Deep Learning," vol. 4, no. 2, pp. 122–129, 2016, doi: 10.18178/foig.4.2.122-129.
- [20] R. B. Aswin, J. A. Jaleel, and S. Salim, "Implementation of ANN Classifier using MATLAB for Skin Cancer Detection," pp. 87–94, 2013.
- [21] A. Bourouis, A. Zerdazi, M. Feham, and A. Bouchachia, "M-health: Skin disease analysis system using smartphone's camera," Procedia Comput. Sci., vol. 19, pp. 1116–1120, 2013, doi: 10.1016/j.procs.2013.06.157.
- [22] N. Ahmed, R. Yasir, A. Rahman, and N. Ahmed, "Dermatological Disease Detection using Image Processing and Artificial Neural Network

- Dermatological Disease Detection using Image Processing and Artificial Neural Network”.
- [23] A. S. Abdulkabi, S. A. M. Najim, and S. A. Khadim, “Eczema Disease Detection and Recognition in Cloud Computing,” vol. 12, no. 24, pp. 14396–14402, 2017.
- [24] D. Filimon and A. Albu, “Skin Diseases Diagnosis using Artificial Neural Networks,” pp. 189–194, 2014.
- [25] M. S. Kolkur, D. R. Kalbande, and V. Kharkar, “Machine Learning Approaches to Multi-Class Human Skin Disease Detection,” vol. 14, no. 1, pp. 29–39, 2018.
- [26] V. Ruthra and P. Sumathy, “Color and Texture based Feature Extraction for Classifying Skin Cancer using Support Vector Machine and Convolutional Neural Network,” pp. 502–507, 2019.
- [27] P. Mirunalini, A. Chandrabose, V. Gokul, and S. M. Jaisakthi, “Deep Learning for Skin Lesion Classification,” 2017, [Online]. Available: <http://arxiv.org/abs/1703.04364>
- [28] J. Hajgude, A. Bhavsar, H. Achara, and N. Khubchandani, “Skin Disease Detection Using Image Processing with Data Mining and Deep Learning,” pp. 4363–4366, 2019.
- [29] S. Akyeramfo-Sam, A. Addo Philip, D. Yeboah, N. C. Nartey, and I. Kofi Nti, “A Web-Based Skin Disease Diagnosis Using Convolutional Neural Networks,” *Int. J. Inf. Technol. Comput. Sci.*, vol. 11, no. 11, pp. 54–60, 2019, doi: 10.5815/ijitcs.2019.11.06.
- [30] A. Mohamed, W. Mohamed, and A. H. Zekry, “Deep learning can improve early skin cancer detection,” *Int. J. Electron. Telecommun.*, vol. 65, no. 3, pp. 507–513, 2019, doi: 10.24425/ijet.2019.129806.
- [31] T. J. Brinker et al., “Deep neural networks are superior to dermatologists in melanoma image classification,” *Eur. J. Cancer*, vol. 119, pp. 11–17, 2019, doi: 10.1016/j.ejca.2019.05.023.
- [32] S. Bhadula, S. Sharma, P. Juyal, and C. Kulshrestha, “Machine Learning Algorithms based Skin Disease Detection,” no. 2, pp. 4044–4049, 2019, doi: 10.35940/ijitee.B7686.129219.
- [33] S. Jinnai, N. Yamazaki, Y. Hirano, Y. Sugawara, Y. Ohe, and R. Hamamoto, “The development of a skin cancer classification system for pigmented skin lesions using deep learning,” *Biomolecules*, vol. 10, no. 8, pp. 1–13, 2020, doi: 10.3390/biom10081123.
- [34] N. Divya and D. P. Dsouza, “Cureskin – Skin Disease Prediction using MobileNet Model,” vol. 3307, pp. 32–37.
- [35] R. C. Maron et al., “Robustness of convolutional neural networks in recognition of pigmented skin lesions,” *Eur. J. Cancer*, vol. 145, pp. 81–91, 2021, doi: 10.1016/j.ejca.2020.11.020.
- [36] K. S. Rao, “Skin Disease Detection using Machine Learning,” vol. 9, no. 3, pp. 64–68, 2021.
- [37] T. Gupta, S. Saini, A. Saini, S. Aggarwal, and A. Mittal, “A Deep Learning Framework for Recognition of Various Skin Lesions due to Diabetes,” 2018 *Int. Conf. Adv. Comput. Commun. Informatics, ICACCI 2018*, no. February 2019, pp. 92–98, 2018, doi: 10.1109/ICACCI.2018.8554897.
- [38] V. S. Kumar and G. S. Jayalakshmi, “Performance analysis of Convolutional Neural Network (CNN) based Cancerous Skin Lesion Detection System Performance analysis of Convolutional Neural Network (CNN) based Cancerous Skin Lesion Detection System”.
- [39] Z. Rayan, M. Alfonse, and A. B. M. Salem, “Machine Learning Approaches in Smart Health,” *Procedia Comput. Sci.*, vol. 154, no. 1985, pp. 361–368, 2018, doi: 10.1016/j.procs.2019.06.052.
- [40] Y. Jiang, S. Cao, S. Tao, and H. Zhang, “Skin Lesion Segmentation Based on Multi-Scale Attention Convolutional Neural Network,” *IEEE Access*, vol. 8, pp. 122811–122825, 2020, doi: 10.1109/ACCESS.2020.3007512.
- [41] P. Pawale, G. Ghadage, and M. Sahani, “Skin disease prediction,” 2021.
- [42] R. Sumithra, M. Suhil, and D. S. Guru, “Segmentation and Classification of Skin Lesions for Disease Diagnosis,” *Procedia - Procedia Comput. Sci.*, vol. 45, no. March, pp. 76–85, 2015, doi: 10.1016/j.procs.2015.03.090.
- [43] T. Majtner, S. Yildirim-Yayilgan, and J. Y. Hardeberg, “Combining deep learning and hand-crafted features for skin lesion classification,” 2016 6th *Int. Conf. Image Process. Theory, Tools Appl. IPTA 2016*, no. April 2021, 2017, doi: 10.1109/IPTA.2016.7821017.
- [44] C. Density, J. T. Davis, and D. E. Brown, “Implementation of Nearest Neighbor using HSV to Identify Skin Disease Implementation of Nearest Neighbor using HSV to Identify Skin Disease,” 2018, doi: 10.1088/1757-899X/288/1/012153.
- [45] A. K. Verma, S. Pal, and S. Kumar, “Classification of Skin Disease using Ensemble Data Mining Techniques,” no. June, 2019, doi: 10.31557/APJCP.2019.20.6.1887.
- [46] M. Takruri, M. K. A. Mahmoud, and A. Al-Jumaily, “PSO-SVM hybrid system for melanoma detection from histo-pathological images,” *Int. J. Electr. Comput. Eng.*, vol. 9, no. 4, pp. 2941–2949, 2019, doi: 10.11591/ijece.v9i4.pp2941-2949.
- [47] J. Sanghavi, “A Novel Approach for Detection of Skin Cancer using Back Propagation Neural Network Jigyasa Sanghavi,” *Helix*, vol. 9, no. 6, pp. 5847–5851, 2019, doi: 10.29042/2019-5847-5851.
- [48] M. Phillips et al., “Assessment of Accuracy of an Artificial Intelligence Algorithm to Detect Melanoma in Images of Skin Lesions,” *JAMA Netw. Open*, vol. 2, no. 10, pp. 1–12, 2019, doi: 10.1001/jamanetworkopen.2019.13436.
- [49] A. Ray, A. Gupta, and A. Al, “Skin Lesion Classification with Deep Convolutional Neural Network: Process Development and Validation,” *JMIR Dermatology*, vol. 3, no. 1, pp. 1–7, 2020, doi: 10.2196/18438.
- [50] S. J. Namitha, N. Nikhilesha, S. S. Bellur, S. S. Sinha, and M. S. Ojus, “Survey on Skin Disease Classification Models,” pp. 6013–6015, 2020.
- [51] R. D. Seeja and A. Suresh, “Deep learning-based skin lesion segmentation and classification of melanoma using support vector machine (SVM),” *Asian Pacific J. Cancer Prev.*, vol. 20, no. 5, pp. 1555–1561, 2019, doi: 10.31557/APJCP.2019.20.5.1555.
- [52] M. Sharma and A. Bhave, “Lesion classification using convolutional neural network,” *Adv. Intell. Syst. Comput.*, vol. 898, no. October, pp. 357–365, 2019, doi: 10.1007/978-981-13-3393-4_37.
- [53] F. Alenezi, A. Armghan, and K. Polat, “A Novel Multi-Task Learning Network Based on Melanoma Segmentation and Classification with Skin Lesion Images,” *Diagnostics*, vol. 13, no. 2, 2023, doi: 10.3390/diagnostics13020262.
- [54] K. Mridha and M. Uddin, “An Interpretable Skin Cancer Classification Using Optimized Convolutional Neural Network for a Smart Healthcare System,” *IEEE Access*, vol. 11, no. March, pp. 41003–41018, 2023, doi: 10.1109/ACCESS.2023.3269694.
- [55] H. Nematzadeh, J. García-nieto, and I. Navas-delgado, “Ensemble-based genetic algorithm explainer with automated image segmentation: A case study on melanoma detection dataset,” vol. 155, no. January, 2023.
- [56] K. A. Muhaba, K. Dese, T. M. Aga, F. T. Zewdu, and G. L. Simegn, “Automatic skin disease diagnosis using deep learning from clinical image and patient information,” *Ski. Heal. Dis.*, vol. 2, no. 1, 2022, doi: 10.1002/ski2.81.
- [57] M. Roshni Thanka et al., “A hybrid approach for melanoma classification using ensemble machine learning techniques with deep transfer learning,” *Comput. Methods Programs Biomed. Updat.*, vol. 3, no. April, p. 100103, 2023, doi: 10.1016/j.cmpbup.2023.100103.
- [58] D. Adla, G. V. R. Reddy, P. Nayak, and G. Karuna, “A full-resolution convolutional network with a dynamic graph cut algorithm for skin cancer classification and detection,” *Healthc. Anal.*, vol. 3, no. December 2022, p. 100154, 2023, doi: 10.1016/j.health.2023.100154.
- [59] M. Arif, F. M. Philip, F. Ajesh, D. Izdrui, M. D. Craciun, and O. Geman, “Automated Detection of Nonmelanoma Skin Cancer Based on Deep Convolutional Neural Network,” *J. Healthc. Eng.*, vol. 2022, 2022, doi: 10.1155/2022/6952304.
- [60] K. Aljohani and T. Turki, “Automatic Classification of Melanoma Skin Cancer with Deep Convolutional Neural Networks,” *Ai*, vol. 3, no. 2, pp. 512–525, 2022, doi: 10.3390/ai3020029.
- [61] M. K. Hasan, M. T. E. Elahi, M. A. Alam, M. T. Jawad, and R. Martí, “DermoExpert: Skin lesion classification using a hybrid convolutional neural network through segmentation, transfer learning, and

augmentation,” *Informatics Med. Unlocked*, vol. 28, 2022, doi: 10.1016/j.imu.2021.100819.

- [62] F. Alenezi, A. Armghan, and K. Polat, “A Novel Multi-Task Learning Network Based on Melanoma Segmentation and Classification with Skin Lesion Images,” *Diagnostics* (Basel, Switzerland), vol. 13, no. 2, Jan. 2023, doi: 10.3390/diagnostics13020262.
- [63] J. Alyami, A. Rehman, T. Sadad, M. Alruwaythi, T. Saba, and S. A. Bahaj, “Automatic skin lesions detection from images through microscopic hybrid features set and machine learning classifiers,” *Microsc. Res. Tech.*, vol. 85, no. 11, pp. 3600–3607, Nov. 2022, doi: 10.1002/jemt.24211.



© 2023 by the Anchal Kumari and Dr. Punam Rattan. Submitted for possible open access publication under the terms and conditions of the Creative Commons Attribution (CC BY) license (<http://creativecommons.org/licenses/by/4.0/>).