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A Systematic Analysis of Skin Cancer Detection Using Machine Learning and Deep Learning Techniques

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Abstract: The skin serves as the primary line for protection against oxidative damage by UV rays on the outside of the body. Skin cancer is now the most often reported malignancy in the world, placing a great effect on economy as well as public health. The most frequent kind of cancer in Caucasians, encompassing both melanoma and non-melanoma, is skin cancer. In this proposed taxonomy, a complete overview of recent developments relevant to cancer diagnosis was discussed. Moreover, a review of melanoma cancer detection methods using machine learning and deep learning with image processing techniques was conducted. It also includes comparison of performance metrics, results, and publicly accessible datasets as well. Conclusion drawn from this study was that deep learning, CNN based models provide more accurate results across variety of datasets among all other machine learning and deep learning models and this also leads directions to the other researchers that which areas will be covered in future.

Keywords: Skin cancer, Deep learning; Classification, Machine Learning.

1. Introduction

The skin, which covers the whole body, is the largest organ in the human body. It is made up of many cell types, including melanocyte cells [1]. Skin cancer, the most common kind of cancer, is on the increase all over the world. A previous study found that climatic variables include global warming, ozone layer and air pollution [2] degradation might raise the peak incidence of skin cancer in the next decades [3]. Certain skin tumors are benign and Melanoma curable if detected early enough and hence seldom proceed to cancer [4]. Early identification is helpful since it allows for strong suggestions for precise and successful treatment regimens but unluckily teams of experts has not satisfied the requirement [5-6].

Public health problem, Cancer is the world's second leading reason of death. Cancer is expected to overtake coronary artery disease coronary artery diseases the main reason of death globally in few coming years [5]. However, as cancer detection and treatment continue to advance concurrently, the number of survivors grows significantly [6]. Cancer is a condition that causes abnormal cell growth and can spread to other sections of the body. Skin cancer is one of the most severe and destructive kinds of cancer [7]. Manual skin evaluation with the naked eye is a time taking and unreliable process [8]. The major goal of researchers is to focus their efforts on developing early cancer detection tools. Dermatoscopy is a common imaging method used by experts. It enlarges the skin lesion's surface, enabling the specialist to inspect its structure more precisely. This strategy, however, can only be used effectively by experienced experts because it is entirely dependent on the professional's vision and expertise [9].

In this study, A categorization of skin cancer detection categorizes into three categories based on machine learning, and deep learning. Melanoma and benign skin cancers are the two primary types of skin cancer, with melanoma being the most dangerous and deadly if detected later [10]. There are some steps involve in skin cancer recognition process. Each step plays vital role in image classification to detect melanoma and non melonma from different datasets. This method includes some stages:

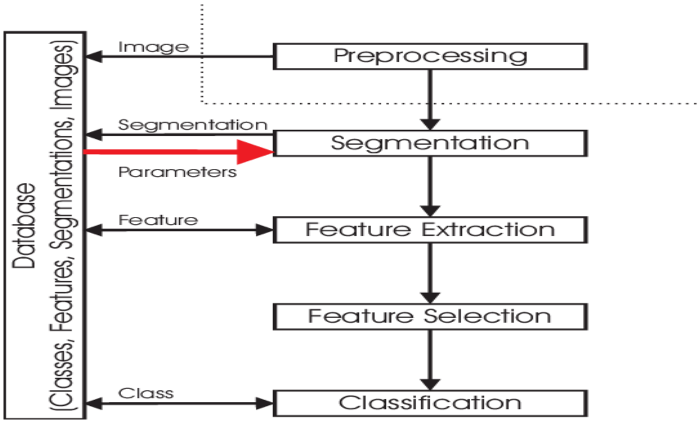

Figure 1. Pattern Recognition

1. Pre-processing: Image resampling, noise and hair removal, color correction and consistency are all performed at this step to provide a clean image [11].
2. Segmentation: The second stage involves segmenting skin cancer liaisons using various approaches and models such as SVM, K Mean clustering, CCN models and gray-level co-occurrence matrix [12-[13].
3. Feature Extraction: During this stage, features are retrieved using several approaches such as ABCD rules with CCN-based model and machine learning-based model [14]–[16].
4. Feature Selection: Following feature extraction, we choose features for categorization. This process involves feature normalization, feature reduction, feature scaling and so on [17], [18].
5. Classification: In the last step of picture recognition pattern, we categorized datasets into melanoma skin cancer disease and non-melanoma skin cancer disease classes using various machine learning (e.g., SVM and forest classifier [18]), AI [19] and deep learning models (i.e. VGG [20-21], DenseNet [22], AlexNet [23] and ResNet [24] etc.).

This paper is organized into six sections. The issues and challenges of paper listed in Section II. Section III introduces the research taxonomy, which provides specific information on papers that fall under several categorized techniques such as machine learning, AI and deep learning. The datasets and performance metrices are discussed in section IV. Discussion and Future Directions have been mentioned in Section V. Section VI discusses the study's Conclusion.

2. Issues and Challenges

To diagnose skin cancer itself a challenging task. According to the recent literature, there are some challenges that still exits are as follow:

Image Quality: The image input quality still influential and low-quality photos such as blurriness, noise, tiny size, lighted and images with some form of reflection on them can result in significant rates of mistake [20][25], [26].

Spot and Skin Color Similarity: Too much extreme skin tone shades also leads to erroneous results due similarity in spot and skin tone color [25], [27].

Loss of information: Shrinking and Cropping of images may sometimes cause loss of information. Image retouching and down sampling also cause loss of information [28-29].

Data Sets: Small data sets cause over-fitting that also leads to erroneous results [29–31].

Accuracy measure: In some cases, system produce best result for hairy images [20]. Also, by increasing the number of layers, disturb the accuracy performance leads to negative factor [31-32].

Accuracy Cost: In some of the latest literature accuracy cost was not measured [26], [32-33].

3. Taxonomy of Detection of Skin Cancer disease

The ultimate purpose of this research is to detect and classify the best approaches, metrics, tools, and classification algorithms for detecting skin cancer in drivers. All primary study data has been classified. Once the empirical investigations are completed, we collect important information and identify research gaps in current research papers. The study's population comprises of research publications on skin cancer detection.

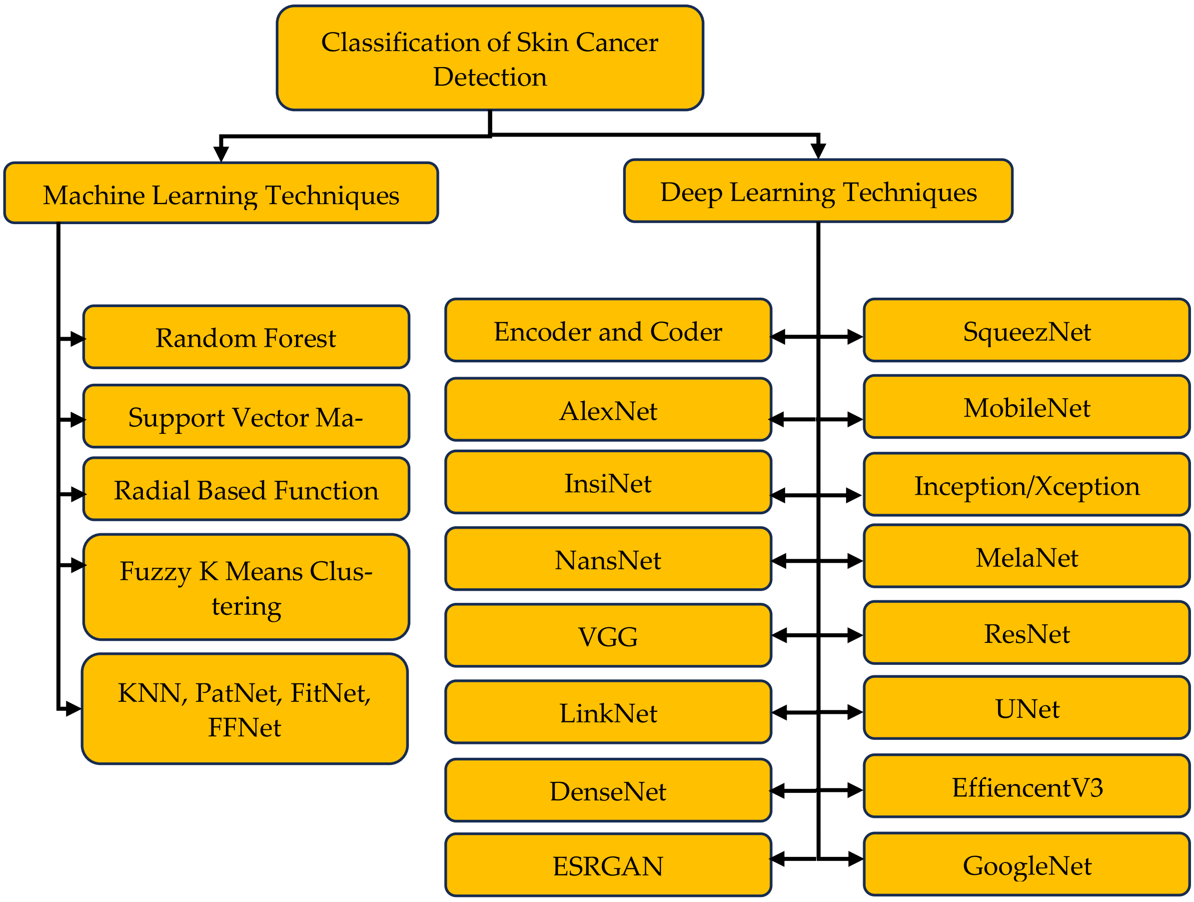

Figure 2. Taxonomy of Detection of Skin Cancer Disease

3.1 Machine Learning Techniques

Skin cancer diagnosis in that suggested study was accomplished using fuzzy k-means clustering and quicker RCNN. PH2 and ISIC Archive datasets are split into major categories: melanoma skin cancer disease and non-melanoma skin cancer disease. Furthermore, the provided technique achieves an average accuracy of 93.15%, 95.4% and 95.6% respectively [25].

A machine learning model with CAD system was Sepehr Salem Ghahfarrokhi et al. proposed. The recommended method extracted the infected area by using ORACM. As an optimization approach, NSGA II, the Genetic Algorithm performs well, while meta-heuristic optimization techniques are employed to eliminate repeated or not needed and minimize the dimension space of feature GLCM. Features were retrieved using Support Vector Machine, Feed-Forward Neural Network, Fitting Neural Network, K-Nearest Neighbor and Pattern Recognition Network. The model was built using MATLAB R2018a. Using PetNet and NSGA II classifier, the PH2 dataset is categorized into classes: melanoma skin cancer disease and non-melanoma skin cancer disease with specificity of 100%, accuracy of 92.24% and sensitivity of 100% achieved [17].

SVM classification and k mean clustering with AI algorithms were used to classify Melanoma and Benign from the local dataset. The algorithm trained on 250 pictures extracted from the local data set. control lesions were showed on 172 pictures, non-melanoma lesions showed on 53 pictures and melanoma lesions detected on 25 pictures [26].

Arslan Javaid et al. suggested machine learning based models Random Forest and SVM for categorizing skin cancer from the publicly accessible ISIC-ISBI 2016 dataset into two primary classes: melanoma and benign. "FEATURESELECT" is MIT-licensed free open-source software for feature selection and implementation. On the ISIC-ISBI2016 dataset, the classification accuracies attained by Quadratic Discriminant, SVM and Random Forest classifiers are 88.17%, 90.84%, 85.50% and 93.89%, respectively [18].

Hatice Catal Reis et al. offer the InSiNet model for detecting benign and malignant lesions in HAM10000 pictures ISIC datasets, which are classified as malignant or benign. The suggested approach was compared to existing ML techniques such as DenseNet-201, ResNet152V2, GoogleNet, EfcientNetB0, RBF, Logistic Regression (LR) and Random Rorest. Architecture of InSiNet (InSiNet + UNet) classified images and achieved high accuracy of 90.54%, 91.89% and 94.59% on ISIC Archive datasets [28].

Duggani Keerthana et al. proposed CNN and SVM combined classifier for determining whether the ISBI 2016 dataset is benign or malignant.firstly received input from both models and give this out to SVM classifier as input. Matlab 2020a was used to simulate the implementation of these concepts. On the open accessible dataset ISBI 2016, the suggested classifier outperformed the CNN models as state of the art. The suggested models were accurate to 88.02% and 87.43%[27].

3.2 Deep Learning Techniques

Deep learning algorithms are proving to be quite effective in the field of medical imaging[34]. Shorfuzzaman et al. investigated the detection of cancer using deep learning and cutaneous image processing in this work. Different architectures based on CCN evaluated including Xception, MobileNetV2, DenseNet201, ResNet152V2, ResNet50V2, VGG16, VGG19 and GoogleNet associated on graphical processing units. These models were used to process on local photos and made a comparison. GoogleNet had the greatest performance accuracy on sets with 74.9% [35].

Hamed Tabrizchi et al. proposed skin cancer diagnosis model based on extended VGG Model and CNN. The ISIC data set was separated into two categories: malignant and benign. The proposed approach was implemented in Keras with bython code and the Scikit-Learn module. For training and testing, Google Colab Pro was utilized. Using this model, they obtain the following results: accuracy 87.07%, sensitivity 85.23% and AUC 92.31. The suggested network would be trained to identify and categorize skin illnesses across several classifications, according to the researchers. During this investigation, the most challenging difficulty was that picture input quality was still relevant and low-quality photos can result in significant rates of mistake [20].

Filali et al. suggested a powerful model to diagnose cancer from PH2 and ISIC datasets by using handcrafted features fusion like (size, structure, texture, and color) and deep learning model for extraction of feature. Datasets PH2 and ISIC were divided into two melanoma and non-melanoma categories. All work in that model was implemented with Matlab 2018. That model gave a significant result 94.69%, 96.63% and 98% for the PH2 and 55.68%, 62.73% and 87.8% for the ISIC dataset by using different performance indicators [29].

Waleed Khalid Al-Azzawi et al. Radiation Circuits were used by researchers to diagnose Melanoma Skin Cancer using CNN. Data was collected from several local sources (such as Shutterstock, istockphoto and geosalud, among others) and classified into five classes: Atopic dermatitis, Plaque psoriasis, Melanoma, Kaposi's sarcoma, and no injuries. This model is built using TensorFlow for mobile apps and Matlab for desktop applications. The application could provide 77% accuracy and 75% precision. The main benefit of this programmed was that it could be accessed without accessing the internet [22].

Ranpreet Kaur et al. Classified Malignant Melanoma through Deep Learning model. CNN was chosen because it provides more accuracy in image and signal processing application [36]. Different datasets were used like PH2, ISBI 2016, ISIB 2017, ISIB 2018 challenges, Mednode DermIS and open access to categorized melinanoma skin cancer disease. The GeForce GTX 1080 Ti hardware arrangement is used for model training. On the ISIC 2016, 2017 and 2020 datasets, that model provided accuracies of 81.41%, 88.23% and 90.42%, respectively. This research categorizes the key flaws of present approaches and suggests areas that require future improvement [37].

Skin cancer diagnosis in that suggested study was accomplished using fuzzy k-means clustering and quicker RCNN. Datasets, PH2, ISBI 2016 and ISIC 2017 categorized into two groups: melanoma skin cancer disease and non-melanoma skin cancer diease. The provided technique had achieved an average accuracy of 93.15, 95.4%and 95.6% respectively [25].

UNet and LinkNet model Segmentaized Melanoma with transfer learning and fine-tuning strategies in the suggested model. The datasets DermIS ,PH2 and ISIC 2018 were categorized into two categories: melanoma skin cancer disease and non-melanoma skin cancer disease. Accuracy measurements include average Dice of 92.35 on PH2 dataset, 89.35 on ISIC 2018 dataset and 87.9% on DermIS dataset [11].

That research conducts a complete analysis of melanoma detection using CNN features. PH2, HAM10000, ISIC 2016 and ISIC 2017 data sets were separated into two categories: melanoma and non-melanoma. The suggested model was implemented using Sklearn packages and Keras in python. Dense-Net-121+MLP 1 with multi-layer perceptron (MLP) obtained accuracy of 98.33% on PH2, 81% on HAM10000, 80.47% on ISIC 2016 and 81.16% on ISIC 2017 datasets [30].

Samira Lafraxo et al. proposed a MelaNet model to categorise benign and malignant on ISBI 2017. Keras framework with Tensorflow in Python was used for model implantation. It was accurate to 87.77% [21].

Walaa Gouda et al. proposed a Targeted Ensemble Machine Classify Model (TEMCM) with an accuracy of 85.7% for categorization of skin cancer into benign and melanoma from the ISIC dataset. TensorFlow Keras was used to implement the Model [24].

To minimise calculations, Adekanmi A. A et al. developed an upgraded CNN combined with encoder-decoder network. The Softmax classifier was used to distinguish between malignant and non-malignant classes in the ISIC 2017 and PH2 datasets. Keras 2, 0.14.1 Version of Scikit-image, TFlearn 0.3 and backend 1.1.0 Tensor flow & and Python 3.5.2 were used to build the model. The suggested model attained the greatest performance measure of on ISIC 2017 dataset was 92% and 95% similarly on the PH2 datasets was 93% and 95% [31].

Mohammad F et al. Use transfer learning to classify the HAM1000 dataset into seven categories: basal cell carcinoma, actinic keratosis & intraepithelial carcinoma, benign keratosis, dermatofibroma, melanoma, vascular and melanocytic nevi. The models were implemented and evaluated using the MATLAB R2021a program. It had the highest total accuracy of 82.9% [32].

Saumya R. S. et al. A fine-tuned EfficientNetB3 model for classifying malignant skin lesions is proposed. It was trained on different models such as InceptionV3, ResNet50, ResNetV2 and EfficientNet B0-B2. All classifications were performed using the ISBI-ISIC 2017 dataset and classified the data into two categories: malignant and benign. All tests were carried out using the Google Colab Python notebook. The EfficientNetB3 model obtained 87.12% accuracy, 87% recall, 87% precision and an F1 score of 85% [26].

This method of study involves developing a Grey-Wolf-Optimization with Hyper-Parameter classified ISIC data set into eight categories: Basal Cell Carcinoma, Melanoma, Actinic Keratosis, Benign, Melanocytic Nevus, Dermatofibroma and Vascular. All experiments are carried out in Python using the Scikit-learn, Keras and Opencv libraries. According to simulation data, the suggested model can offer testing accuracy of up to 98.33% [33].

Hatice Catal Reis et al. offer the InSiNet model for detecting benign and malignant lesions in HAM10000 pictures ISIC datasets, which are classified as malignant or benign. The suggested approach was compared to existing ML techniques such as DenseNet-201, ResNet152V2, GoogleNet, EfcientNetB0, RBF, Logistic Regression (LR) and Random Rorest. Architecture of InSiNet (InSiNet + UNet) classified images and achieved high accuracy of 90.54% , 91.89% and 94.59% on ISIC Archive datasets[28].

Bilge S. et al. investigated the impact of hair marks and picture quality on melanoma classification using CNN models: DenseNet121, VGG16, ResNet50 and AlexNet. In this work, a synthetic picture dataset was utilized to identify melanoma images more accurately than benign photos under contrast changes and the ResNet model was suggested when image contrast was a concern. Noise cause lower detection of melanoma as compared to benign tumors. Furthermore, these groups are susceptible to blurriness. DenseNet delivers the maximum accuracy in noisy and fuzzy datasets. In this group, the photos with rulers have poorer precision, whereas ResNet has greater accuracy. The model evaluated the accuracy of 86% on ruler set, 89.22% on hair set and 88.81% on that set which contain neither ruler nor hairy images [23].

Qaiser Abbas et al. introduced NASNet which trained on the ISIC 2020 dataset that classifies data into two categories: melanoma skin cancer disease and non-melanoma skin cancer disease. Keras with Tensor flow backend and Keras with an accuracy of up to 97% were used in the implementation [38].

Melanoma segmentation methods based on UNet and LinkNet deep learning networks were integrated with transfer learning and fine-tuning strategies in the suggested model. The datasets DermIS, PH2 and ISIC 2018 categorized into two categories: melanoma and non-melanoma. Average accuracy 92.3% on PH2 dataset, 89.3% in ISIC 2018 and 87.9% on the DermIS dataset [39].

Rupali Kiran Shinde et al. combined an IoT based device (Raspberry Pi 4) with NeoPixel 8-bit LED ring and spy camera to identify benign and malignant cells using Squeeze-MNet and MobileNet models trained on the ISIC dataset. The average precision was 98.02%. Using the ISIC dataset, algorithm of hair removal enhanced the accuracy of skin cancer diagnosis to 99.36% and AUC-ROC to 98.9% [40].

4. Datasets and Performance Metrices

In this Section a detailed analysis on datasets and performance metrices is done.

4.1 Publicaly Available Datasets

ISIC Archive: Many medical and dermoscopic lesion datasets from throughout the world are available in the ISIC archive gallery, including the ISIC Challenges dataset, ISIB and HAM10000 [41].

PH2 database: It consists of professional dermatologists performing clinical diagnosis, identification, and manual segmentation of different dermoscopic features on a set of 200 dermoscopy images pictures [42].

Med-Node: The dataset contains 70 pictures of melanoma disease and 100 pictures of non-melanoma disease from the dermatology department's collection at Medical Centre Groningen University [43].

DermIS: The first is a subset of a DermIS database with 43 macroscopic pictures of lesions classified as melanoma and 26 as non-melanoma [44].

Local Dataset: Different dermatologist, hospitals, outpatient clinics, labs and surgery facilities collect local data sets.

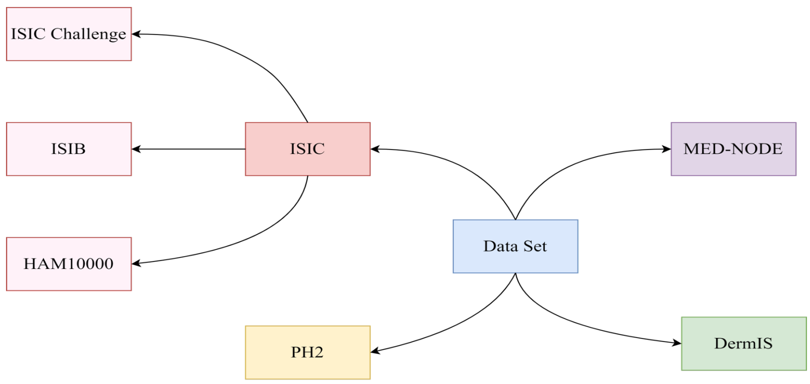

Figure 3. Dataset

4.2 Performance Metrices

A set of measuring performance that are often used to assess and contrast alternative methodologies. These performance measures are used to assess performance: sensitivity, specificity, precision, accuracy, AUC and Jacurad /F-score. Values of the following Table 1 are produced using the following criteria:

Performance Measures is lie under 90% to 100% refers to High performance.

Performance Measures is lie under 80% to 89% refers to Medium performance.

Performance Measures is below from 80% refers to Low performance.

Table 1. Analysis of Performance Matrices

Research paper	Data Set	Classifier	Sensitivity	Specificity	Precision	Accuracy	AUC	Similarity Measures
Improved VGG Model	ISIC	VGG-16	Medium	×	×	Medium	High	High (F-Score)

(Hamed Tabrizchi et al. 2022) [20]									
Efficient fusion of hand-crafted and pre-trained CNNs (Youssef Filali et al. 2020) [29]	ISIC	SVM & CNN	Low	High	Low	Medium	×	Low (F-Score) Low (Kappa)
	PH2	SVM & CNN	High	High	High	High	×	High (F-Score)
Radiation Circuits for Diagnosis (Waleed Khalid Al-Azzawi et al. 2022) [22]	Local	CNN	×	×	Low	Low	×	×
LCNet (Ranpreet K et al. 2022) [37]	ISIC 2016	DCNN	Medium	×	Medium	Medium	×	Medium (F-Score)
	ISIC 2017	DCNN	Medium	×	Low	Medium	×	Low (F-Score)
	ISIC 2020	DCNN	High	×	High	High	×	High (F-Score)
Deep learning and fuzzy k-means clustering(Mariam Nawazat et al.	ISBI 2016	VGG-16, RCNN	High	High	×	High	×	×
	ISIC 2017	VGG-16, RCNN	×	High	×	High	×	×
	PH2	VGG-16, RCNN	×	High	×	High	×	×

2021) [25] stacked ensemble of deep learning models (Mohammad Shorfuzzaman et al. 2021) [35]	ISIC	DenseNet121, EfcientNetB0 and Xcept-ion	High	×	×	High	High	High (F-Score)
	ISIC 2018	U net	Medium	High	×	High	High	Medium (F-Score) Medium (**JAC**)
Transfer learning & Fine tuning (Rafael Luz Araújo el at. 2021) [11]	DermIS	U net	Medium	High	×	High	High	Medium (F-Score) Low (**JAC**)
	PH2	U net	High	High	×	High	High	High (F-Score) Medium (**JAC**)
Comprehensive analysis via Deep CNN features (Himanshu K. Gajera et al. 2022) [30]	ISIC 2016	DenseNet-121+MLP	Low	Medium	Low	Medium	×	Low (F-Score)
	ISIC 2017	DenseNet-121+MLP	×	×	×	Medium	×	×
	HAM10000	DenseNet-121+MLP	×	×	×	Medium	×	×
	PH2	DenseNet-121+MLP	High	High	×	High	×	×
Machine Learning method combination of	PH2	NSGA II and Pattren Net	High	High	×	High	×	×

nonlinear and texture features (Sepehr Salem Ghahfarrokhi et al. 2022) [17]								
CNN:MELANet (Samira Lafraxo et al. 2022) [21]	ISIB 2017	MELA Net	High	High	×	High	High	High (F-Score)
	MED-NODE	MELA Net	Medium	Medium	×	Medium	High	Medium (F-Score)
	PH2	MELA Net	High 97.82%	High 97%	×	High	High	High (F-Score)
CNN: Resnet50, InceptionV3 and Inception Resnet (Walaa Gouda et al. 2022) [24]	ISIC 2018	InceptionV3	×	×	×	Medium	×	×
Artificial Intelligence Algorithm with SVM Classification (Vivekanadam Balasubramaniam et al. 2021) [19]	Local	SVM	×	×	×	Low	×	×
DCCN: Encoding-	ISIC 2017	Encoder Decoder	High	High	×	High	×	High (F-Score)

Decoding Network (Adekanmi A. ADEGUN et al. 2020) [31]	PH2	CNN Model	High	High	×	High	×	High (F-Score)
Deep Transfer Learning 13 Models (Mohammad Fraiwan et al. 2022) [32]	HAM10000	Dense Net	×	High	Low	Medium	×	×
IMPROVED EFFICIENT-NETB3 (Saumya R. Salian et al. 2022) [44]	ISIB 2017	Efficient-NetB3	×	×	Medium	Medium	×	Medium (F-Score)
	ISIC 2017	Efficient-NetB3	×	×	Medium	Medium	×	Medium (F-Score)
Grey Wolf Optimization (Rasmiranjan Mohakud et al. 2022) [33]	ISIC	CNN	×	×	×	High	×	High (F-Score)
ML: Random Forest Classifier (Arslan Javaid et al. 2021) [18]	ISIC 2017	SVM and Random Forest	×	×	×	High	×	×
	ISIB 2017	SVM and Random Forest	×	×	×	High	×	×
DCCN: InSiNet	ISIC 2018	InSiNet	High	High	×	High	×	High (F-Score)

(Hatice Catal Reis et al. 2022) [28]	ISIC 2019	InSiNet	High	High	×	High	×	High (F-Score)
	ISIC 2020	InSiNet	High	Medium	×	High	×	High (F-Score)
melanoma-index based-entropy-features (Kang Hao Cheong et al. 2021) [45]	ISIC 2016	SVM-RBF	High	High	×	High	×	×
	DermQuest	SVM-RBF	High	High	×	High	×	×
	DermIS	SVM-RBF	High	High	×	High	×	×
CNN: ResNet50, DenseNet121, VGG16 and AlexNet (Bilge S. Akkoca Gazioglu et al. 2021) [23]	ISIC	ResNet50, DenseNet21, VGG16, AlexNet	×	×	×	Medium	×	×
NASNet (Qaiser Abbas et al. 2022) [38]	ISIC 2020	NASNet	×	×	High	High	×	High (F-Score)
U-net and LinkNet (Syed Inthiyaz et al. 2023) [39]	PH2	U-net and LinkNet	×	×	×	Medium	Medium	High (F-Score)
	ISIC 2018	U-net and LinkNet	×	×	×	Medium	Medium	Medium (F-Score)
	DermIS	U-net and LinkNet	×	×	×	Medium	Medium	Medium (F-Score)

CNN with SVM (Duggani Keerthana et al. 2023) [27]	ISIB 2016	CNN and SVM	×	×	×	Medium	×	High (F-Score)
Squeeze-MNet (Rupali Kiran Shinde et al. 2022) [40]	ISIC	SQUEEZ-Mnet	×	×	×	High	High	High (F-Score)

True Positive (TP), True Negative (TN), False Positive (FP) and False Negative (FN) parameters generated using confusion matrix to obtained performance matrices. The number of lesion samples accurately diagnosed as melanoma was indicated by TsP, whereas the number of non-melanoma lesion samples is represented by TN. FN indicates photos that were wrongly identified as non-melanoma when they were melanoma, whereas FP shows the fraction of samples that were incorrectly labelled as melanoma [4]. Accuracy is calculated using the proportion of properly recognized samples and the total number of predictions based on these characteristics.

$$\text{Accuracy} = \frac{\text{TP} + \text{TN}}{\text{TF} + \text{FN} + \text{FP} + \text{TP}} \tag{1}$$

Other parameters, Precision and Sensitivity, are very important metrics used to evaluate the model's performance because Precision measures all positive predicted rates[36].

$$\text{Precision} = \frac{\text{TP}}{\text{TP} + \text{FP}} \tag{2}$$

Sensitivity, on the other hand, computes the true positive ratio from all positively identified samples[46].

$$\text{Sensitivity} = \frac{\text{TP}}{\text{FN} + \text{TP}} \tag{3}$$

Specificity is a metric that measures the model's ability to detect TN in each class[47].

$$\text{Specificity} = \frac{\text{TN}}{\text{TN}+\text{FP}} \tag{4}$$

F1-Score computes the harmonic mean of Precision and Sensitivity while accounting for FP and FN. Its value close to 1 indicates that the Precision and Sensitivity are perfect[1].

$$\text{F} - \text{Score} = \frac{2\ (\text{Precision} \times \text{Sensitivity})}{\text{Precision} + \text{Sensitivity}} \tag{5}$$

Whereas Jacquard measure is used to check similarity among two datasets of population.

$$\text{JAC} = \frac{\text{TP}}{\text{TP+ FP+ FN}} \quad (6)$$

Moreover, kappa used to measure the robustness of the dataset.

$$\text{Kappa} = \frac{\text{Total Acuuracy} - \text{Random Accuracy}}{1 - \text{Random Accuracy}} \quad (7)$$

$$\text{Random Accuracy} = \frac{(\text{TN + FP})\times(\text{TN + FP})(\text{FN + TP})\times(\text{FP+ TP})}{\text{Total} \times \text{Total}} \quad (8)$$

5. Discussion and Future Directions

This study classified different studies on skin cancer detection using deep learning and machine learning models. Table.1 summarizes the performance analysis of all models based on various methodologies. In machine learning, SVM-based papers had high accuracy, specificity, precision, and sensitivity, but f score test was medium on PH2 and ISIC datasets but in certain cases accuracy was poor when local dataset used. According to table.1 this study concluded that several models were built in comparison to the machine learning technique to identify skin cancer and provided more accurate findings. Furthermore, CCN-based papers work on hair detection in order to provide more accurate outcomes in hair removal. That is why papers using deep learning algorithms had higher outcomes in terms of accuracy measures. Deep learning models using ISIC datasets achieve excellent levels of accuracy, sensitivity, specificity, area under the ROC curve and f score, whereas deep learning models with PH2 datasets achieve similar levels of performance. At the same time, another article utilized the Jacquard measure to compare the similarity of two population datasets and kappa informs us that the dataset's resilience under all data sets was medium in its results. On the other hand, the med node data set provides findings ranging from medium to high. Based on its range, this study produced mediocre outcomes when using DermIs. The strength of this work is it provides extensive understanding of recent machine learning and deep learning model. The study's contribution is that the CNN technique may be used while working on local data sets to enhance the results provided by performance measurements. The next goal of this research is to improve accuracy using a more efficient deep learning model. These deep learning models can also be used to identify other diseases. Furthermore, we may connect these models for server-less computers to reduce computational costs.

6. Conclusion

After cardiovascular disease, skin cancer is the greatest cause of mortality. It may be feasible to cure it if it is identified in its early stages. This study divided many studies into machine learning, deep learning and AI-based models. Machine learning methods such as SVM, K Mean Clustering, Fuzzy K Mean Clustering and the Random Forest technique were examined on the ISIC, DermIS, MED NODE and PH2 datasets, yielding medium to high-rate outcomes utilizing performance measures. After cardiovascular disease, skin cancer is the greatest cause of mortality. It may be feasible to cure it if it is identified in its early stages. This study divided many studies into machine learning, deep learning and AI-based models. Machine learning methods such as SVM, K Mean Clustering, Fuzzy K Mean Clustering and the Random Forest technique were examined on the ISIC, DermIS, MED NODE and PH2 datasets, yielding medium to high-rate outcomes utilizing performance measures. When testing artificial intelligence findings on a local dataset, the results are poor. Furthermore, deep learning models such as MelaNet, ResNet, DenseNet, Inception, xception, VGG, InsiNet and hybrid models outperformed machine learning and artificial intelligence studies on ISIC, Med Node, PH2 and DermIS. Finally, this study concludes that deep learning models outperform techniques in terms of many quality indicators such as sensitivity, accuracy, F-Score, specificity, and precision. In the future, we plan to investigate the efficacy of reinforcement learning-based systems for skin cancer diagnosis.

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