PREVALENCE STUDY FOR DETECTING SKIN LESIONS ON MACHINE LEARNING & DEEP LEARNING MODELS

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Abstract: Skin lesions disease like moles, are commonly observed in the general population and can potentially be indicative of different skin conditions, as well as skin cancer. Early detection of skin lesions can improvise the prediction of such conditions, making it important to develop efficient methods for detection. In this study, we conducted a prevalence study to detect skin lesions utilizing machine learning modules and ResNet architecture. The study utilized a large dataset of skin lesion disease images. The images were pre-processed and used to train different machine learning modes, including Convolutional Neural Networks (CNNs) with ResNet architecture. The outcomes of the models were evaluated using various evaluation metrics, including accuracy, sensitivity, and specificity. Our results demonstrated that the ResNet-based CNN models outperformed other machine learning models. Our findings highlight the potential of machine learning models and ResNet architecture for detecting skin lesions. Further research could focus on optimizing the models for real-world implementation and assessing their generalizability in diverse populations.

Keywords: Melanoma, Seborrheic keratosis, Nevus, Gradian Boosting, Random Forest, ResNet 18,50,101,152.

1. Introduction

Skin cancer becomes a common disease all over the world. It occurs through occupies multiplying of a body cell in an uncontrolled manner and it the peripheral tissues. Skin lesion is less frequent but it has the highest mortality rate. There are three types of skin cancer: Malignant Melanoma, Squamous cell carcinoma, and Basal cell carcinoma. Melanoma is the most hazardous type of these types and it occurs due to a high metastatic rate. Melanoma is a type of malignancy that mainly occurs in white people, for men which are seen in the trunk, and for women in the lower limb, it can develop and grow on the epidermal upper layer of the skin and presumably may also affect the chest and back of the body [13]. Melanoma causes by melanin which is developed from melanocytes. Also, melanoma type grows more rapidly than other cancer types and it occurs due to excessive ultraviolet rays which are commonly seen in most Europe countries [2]. These two types are non-melanoma types although both types melanoma and nonmelanoma are dangerous variants of skin cancer.

CNN and other Deep Learning methods which are spread rapidly, have bought a good opportunity for non-experts and non-professionals to turn much more well-known with deep learning tools and to realize their Operational principles. Skin cancer can be detected through a machine-learning process [6]. This classification process helps physicians to test the primary stage of skin cancer (e.g. [5],[6]). Although it is very challenging to detect images of skin lesions. Pre-processing, image segmentation, and future extraction all are done in this project. Different ML techniques as SVM, Random Forest, and PCA are used for the prognosis of skin disease (e.g. [3],[4]).

Nowadays in machine learning the classifying of abnormal tissue skin has become an aim. Before 2016 various researchers took up this machine learning procedure and dispersion, feature extrication, and categorization [1]. The phases are:

(i)Image enhancement: Using this process all the noise i.e., here and blood vessels from the thermoscopic images has been removed. (ii)Segmentation: Segmentation is a vital step in the CAD system. For a large number of abnormal tissues, this process becomes more complex. It became a more tiring task in the CAD system. (iii) Feature extraction: It is also an important process to identify the best set of features in high intolerance capability to categorize the dataset into many classes. (iv)Detection and categorization: In our system dataset is classified according to the capability of the system. So, it's totally depending upon the superiority of the classifier [4].

The main handout of this paper is: (1) we use machine learning and deep learning models for accurate skin lesion categorization in thermoscopic images [8]-[9]. Residual learning enables the network to become deep, helps the network focus more on semantically important regions, and thus improves its ability for discriminative representation; (2) We have used CNN-based Residual models in our project which is advantageous for the categorization of Skin cancer. (3) we achieve the state-of-the-art skin lesion categorization performance on the ISIC-skin 2016 and 2017 datasets which is important for computer-aided recognition of skin lesions.

In section 2 we briefly describe the review of some related works of Skin lesion disease. In section 3 we describe the Scope of review of our paper. In section 4 we describe the system framework. In section 5 we describe our required materials and methods. in section 6 we discuss the parameters of the evaluation and in section 7 we describe the CNN architecture. In sections 8 and 9 we describe our proposed methodology and Experiment methodology respectively. In section 10 we can get the result analysis and in section 11 we conclude our work.

2. Background of the Work

In recent years Skin lesion classification using CNN-based Deep Learning or Machine learning modules expressed in the above fig. is very much famous nowadays. Earlier various research workers worked in this domain and made remarkable contributions. In the year 2020, Zabir Al Nazi and Tasnim Azad Abir worked on the U-Net and Dense-Net based on deep learning methods like SVM, Random Forest, and Decision Tree Adaboost and obtained an accuracy of about 90%. After that, Ammara Masood, and Adel Ali Al-Jumaily worked on ANN, CART, LDA, etc to get an accuracy of about 82.9% on the D.A, ANN model. Again, Noel Codella, Junjie Cai, Mani Abedini, Rahil Garnavi, Alan Halpern, and John R. Smith worked on various methods like 4K FC6, Esemble, 1K FC8, Fusion, GRAY, RGB, etc. They obtained the highest accuracy on their combined model which is about 73.9%. Zhiwei Qina, Zhao Liu, Ping Zhua, and Yongbo Xuea also worked on deep learning methods using Generative Adversarial Networks (GANs) like ResNet 50, CNN, and Transfer ResNet 50, and obtained their highest accuracy on Transfer ResNet 50, the model.

Table I: Related Work for All Researchers

SLNO.	PAPER NAME	YEAR OF PUBLICATION	MODEL NAME	METHODS/ ARCHITECTURE	ACCURACY
1	Zabir Al Nazi and Tasnim Azad Abir Springer Nature Singapore Automatic Skin Lesion Segmentation and Melanoma Detection: Transfer Learning Approach with U-Net and DCNN-SVM	2020	U-Net, DenseNet201	SVM	0.92 ± 0.14
				Random forest	0.84 ± 0.10
				Decision tree	0.83 ± 0.13
				AdaBoost	0.91 ± 0.13
				Gradient boosting	0.84 ± 0.17
2	MARWAN ALI ALBAHAR IEEE Access Skin Lesion Classification using Convolution Neural Network with Novel Regularizer	2019	CNN +Novel Regularizer	CNN	97.49
3	Jianpeng Zhang, Yutong Xie, Yong Xia , and Chunhua Shen IEEE NPSS Attention Residual Learning for Skin Lesion Classification	2019	ARL-CNN50	Melanoma	0.837
				Seborrheic Keratosis	0.908
4	Mohammed A. Al-masni a, Dong-Hyun Kima, Tae-Seong Kimb, ELSEVIER Multiple skin lesions diagnostics via integrated deep convolutional networks for segmentation and classification	2020	Inception-v3		77.04
			ResNet-50		79.95
			Inception-ResNet-v2		81.79
			DenseNet-201		81.27
5	Shunichi Jinnai [1,*] , Naoya Yamazaki [1], Yuichiro Hirano [2], Yohei Sugawara [2], Yuichiro Ohe [3] and Ryuji Hamamoto Biomolecules The Development of a Skin Cancer Classification System for Pigmented Skin Lesions Using Deep Learning	2020	six classes	**FRCNN**	86.2
				BCDs	79.5
				TRNs	75.1
			two classes	**FRCNN**	91.5
				BCDs	86.6
				TRNs	85.3
6	Germán Capdehourat , Andrés Corez , Anabella Bazzano , Rodrigo Alonso , Pablo Musé ELSEVIER Toward a combined tool to assist dermatologists in melanoma detection from dermoscopic images of pigmented skin lesions	2011	Automatic	AdaBoost – C4.5	0.977
				SVM	0.953
			Manual	AdaBoost – C4.5	0.982
				SVM	0.948
7	M. Emre Celebi, Senior Member, IEEE, and Azaria Zornberg IEEE SYSTEMS JOURNAL Automated Quantification of Clinically Significant Colors in Dermoscopy Images and Its Application to Skin Lesion Classification	2014	SYMBOLIC REGRESSION EQUATIONS Weight(w)	0.125	56.23
				0.250	71.72
				0.375	59.26
				0.500	52.53
8	Launcelot C. De Guzman, Ryan Paolo C. Maglaque, Vianca May B. Torres, Simon Philippe A. Zapido and Macario O. Cordel II Third International Conference on Artificial Intelligence Design and Evaluation of a Multi-model, Multi-level Artificial Neural Network for Eczema Skin Lesion Detection	2015	Eczema vs Non-Eczema	Single Level	87.30%
				Multi-level, Multi Model	85.71%
9	Mohamed A. Kassem, Khalid M. Hosny, Robertas Damaševi˘cius and Mohamed Meselhy Eltoukhy Diagnostics Machine Learning and Deep Learning Methods for Skin Lesion Classification and Diagnosis: A Systematic Review	2021	Deep Learning and Machine Learning Algorithms	ABCD, MLP	88.0%
				KNN	94.0%
				ABCD, SVM	90.0%
				spectroscopy, PCA, KNN, SVM	76.84%
				K-means, pixel-based classification	89.42%
10	Toma´s Majtner, Sule Yildirim-Yayilgan, Jon Yngve Hardeberg ˇ IEEE Combining Deep Learning and Hand-Crafted Features for Skin Lesion Classification	2016	Deep Learning methods	First SVM Classifier	0.794
				Second SVM Classifier (AlexNet)	0.805

11	Ali Madooei, Mark S. Drew, Maryam Sadeghi, and M. Stella Atkins School of Computing Science Simon Fraser University Intrinsic Melanin and Hemoglobin Colour Components for Skin Lesion Malignancy Detection	2012	Support Vector machine (SVM)	Malignant vs. Benign	0.953
				Melanoma vs. Benign	0.946
				Melanoma vs. Spitz Nevus	0.960
12	Rashika Mishra, Ovidiu Daescu IEEE Bioinformatics and Biomedicine Deep Learning for Skin Lesion Segmentation	2017	CNN	Proposed CNN architecture	0.928
				Otsu segmentation	0.884
				Yading Yuan	0.934
				Matt Berseth	0.932
				Lei Bi	0.934
13	Ilker Ali OZKAN, Murat KOKLU International Journal of Intelligent Systems and Applications in Engineering Skin Lesion Classification using Machine Learning Algorithms	2017	PH^2 Dataset using machine learning methods	ANN	92.50%
				SVM	89.50%
				KNN	82.00%
				DT	90.00%
14	Kashan Zafar, Syed Omer Gilani, Asim Waris , Ali Ahmed, Mohsin Jamil, Muhammad Nasir Khan, Amer Sohail Kashif Sensors Skin Lesion Segmentation from Dermoscopic Images Using Convolutional Neural Network	2020	CNN models using PH^2 dataset	FCN-16s	0.802
				DeeplabV3+	0.814
				Mask-RCNN	0.830
				Res-Unet	0.854
15	Jinen Daghrir, Lotfi Tlig, Moez Bouchouicha, Mounir Sayadi ATSIP Melanoma skin cancer detection using deep learning and classical machine learning techniques: A hybrid approach	2020	melanoma skin cancer from the ISIC dataset.	KNN	57.3%
				SVM	71.8%
				CNN	85.5%
				Majority Voting	88.4%
16	Md. Kamrul Hasan, Lavsen Dahal, Prasad N. Samarakoon, Fakrul Islam Tushar, Robert Martí Computers in Biology and Medicine DSNet: Automatic dermoscopic skin lesion segmentation	2020	ISIC-2017 test dataset	Melanoma	0.928
				Seborrheic keratosis	0.917
				Nevus	0.970
			PH2 dataset	Melanoma	0.955
				Seborrheic keratosis	0.996
				Nevus	- -
17	Le Thu Thao, Nguyen Hong Quang Asia Pacific Symposium on Intelligent and Evolutionary Systems Automatic skin lesion analysis towards melanoma detection	2017	ISBI test dataset	Simple Conv-Net architecture	0.515
				VGG-16 using transfer learning	0.837
18	Noel Codella, Junjie Cai, Mani Abedini, Rahil Garnavi, Alan Halpern, and John R. Smith Springer International Publishing Switzerland Deep Learning, Sparse Coding, and SVM for Melanoma Recognition in Dermoscopy Images	2015	Hand Coded	Ensemble	0.715
			Caffe CNN	4K FC6	0.723
				1K FC8	0.654
				Fusion	0.725
			Sparse Coding	GRAY	0.651
				RGB	0.681
				Fusion	0.695
			Fusions	Deep	0.728
				All	0.739
19	Adegun Adekanmi Adeyinka(B) and Serestina Viriri CrossMark Skin Lesion Images Segmentation: A Survey of the State-of-the-Art	2018	ISBI Challenge for Skin Lesion Segmentation	Deep convolutional networks	0.932
				Deep learning network	0.922
				K-means clustering	0.900
				Deep CNN	0.829
20	Sertan Kaymak, Parvaneh Esmaili, and Ali Serener, Member NEURAL Deep Learning for Two-Step Classification of Malignant Pigmented Skin Lesions	2018	AlexNet	MELANOCYTIC AND NON-MELANOCYTIC SKIN LESIONS	78%
				MELANOMA AND MELANOCYTIC NEVUS	83.8%
				NON-MELANOCYTIC MALIGNANT AND BENIGN	58%

21	Amirreza Mahboda, Gerald Schaefer, Chunliang Wang, Georg Dorffner, Rupert Ecker, Isabella Ellinger ELSEVIER Transfer learning using a multi-scale and multi-network ensemble for skin lesion classification	2020	EfficientNet and SeResNeXt-50 models.	MSM-CNN algorithm,	95.8%
22	Ammara Masood, Adel Ali Al-Jumaily International Journal of Biomedical Imaging Computer Aided Diagnostic Support System for Skin Cancer: A Review of Techniques and Algorithms	2013	Deep Learning methods	D.A, ANN	82.9%
				CART	80.0%
			Machine Learning methods	LDA + KNN + decision tree	70.0%
				Multiple classifiers (SVM, GML, kNN)	75.69%
23	Zhiwei Qina, Zhao Liub, Ping Zhua, Yongbo Xuea ELSEVIER A GAN-based image synthesis method for skin lesion classification	2020	Generative Adversarial Networks (GANs)	CNN	0.936
				ResNet50	0.936
				Transfer ResNet50	0.944
				Transfer-ResNet50 with data augmentation.	0.952
24	Rita Francese1, Maria Frasca1, Michele Risi, Genovefa Tortora Journal of Real-Time Image Processing A mobile augmented reality application for supporting real-time skin lesion analysis based on deep learning	2021	Adopted CNN model	CNN classifcation results	78.8%
25	Devansh Bisla, Anna Choromanska, Jennifer A. Stein, David Polsky, Russell Berman New York University School of Medicine SKIN LESION SEGMENTATION AND CLASSIFICATION WITH DEEP LEARNING SYSTEM	2019	Data Generation Network with de-coupled DCGANs	Classification Model but without performing data purification at testing	0.675
				Classification Model	0.717
26	Ulzii-Orshikh Dorj, Keun-Kwang Lee, Jae-Young Choi, Malrey Lee Springer Science+Business Media The skin cancer classification using deep c neural network	2018	ECOC SVM	Actinic Keratoses	92.3%
				Basal cell carcinoma	91.8%
				Squamous cell carcinoma	98.1%
				Melanoma	97.2%
27	Philippe M. Burlina, Neil J. Joshi, Elise Ng, Seth D. Billings, Alison W. Rebman, John N. Aucott Computers in Biology and Medicine Automated detection of erythema migrans and other confounding SKIN lesions via deep learning	2018	ResNet50 DCNN model	4-Class	82.79%
				2-Class	86.53%
				Clinical positive examples only	71.55%
28	Gil Yosipovitch, MD; Kyle C. Mills, MD; Leigh A. Nattkemper, MS; Ashley Feneran, DO; Hong Liang Tey, MD; Brett M. Lowenthal, MD; Daniel J. Pearce, MD; Phillip M. Williford, MD; Omar P. Sangueza, MD; Ralph B. D'Agostino Jr, PhD Research Association of Pain and Itch With Depth of Invasion and Inflammatory Cell Constitution in Skin Cancer Results of a Large Clinicopathologic Study	2023	Depth of Invasion and Inflammatory Cell	BCC basal cell Carcinoma	46.6%
				SCC subcutaneous carcinoma.	42.5%
29	Rania Ramadan, Saleh Aly, and Mahmoud Abdel-Aty Sohag Journal of Science An Efficient Skin Lesion Segmentation Using Deep Fully Convolutional Neural Network with Gradient Skin Images	2013	Using Deep Fully Convolutional Neural Network with Gradient Skin Images	U-Net	90.70%
				AttU-Net	93.76%
				ResUNet++	93.82%
				Ftl	94.12%
				Eru	94.35%
				Dagan	93.24%
				CKT-Net	94.92%
				FAT-Net	95.78%
30	Doaa A. Shoieb, Sherin M. Youssef, Walid M. Aly, Journal of Image and Graphics Computer-Aided Model for Skin Diagnosis Using Deep Learning	2016	Deep Learning	Melanoma	96.04%
				Basal Cell Carcinoma	96.15%
				Eczema	94.12%
				Impetigo	91.42%

Scientists like Shunichi Jinnai, Naoya Yama zaki, Yuichiro Hirano, Yohei Sugawara, Yuichiro Ohe, Ryuji Hamamoto worked on the methods like FRCNN, BCDs, TRNs, FRCNN, BCDs, TRNs and obtained their highest accuracy of 91.1% at FRCNNs. Ulzii-Orshikh Dorj, Keun-Kwang Lee, Jae-Young Choi, and Malrey Lee Worked on ECOC SVM on several diseases and obtained their highest accuracy in the detection of Squamous cell carcinoma which is 98.1%. Amirreza Mahboda, Gerald Schaefer, Chunliang Wang, Georg Dorffner, Rupert Ecker, and Isabella Ellinger worked on EfficientNet and SeResNet-50 methods based on the MSM-CNN algorithm and obtained an accuracy of 95.8%. Le Thu Thao and Nguyen Hong Quang worked on the VGG-16 using transfer learning and Simple Conv-Net architecture and obtained an accuracy of 83.7%. AlexNet model of deep learning was used by Sertan Kaymak, Parvaneh Esmaili, Ali Serener, Member and they obtained an accuracy of 83.8% on MELANOMA AND MELANOCYTIC NEVUS disease detection. Germán Capdehourat, Andrés Corez, Anabella Bazzano, Rodrigo Alonso, and Pablo Musé used the methods of AdaBoost– C4.5 manually and automatically where the highest accuracy of 98.2% was taken from the automatic model (e.g. table 1).

3. Scope of Review

In every work, we can observe that either machine learning modules or deep learning models are used for the classification of skin lesion diseases like melanoma, seborrheic keratosis, and nevus. In our opinion, only one type of detection method is not as good as the combination of both Deep Learning & Machine Learning methods. This combination helps to find out these data in a much more stable way. That's why in our work, we have used both Machine Learning & Deep Learning models which help to the detection and categorization of skin lesion disease more accurately.

4. System Framework

At first, we collect our dataset, and then the data set is getting ready for data cleaning. Then the data is done to be segmented into various types and after the segmentation, the feature extraction of this data is divided into two parts Train data and Test data. After that, our model is ready for training and we can take the performance evaluation process of all models and the trained model is give the result of skin lesion (e.g. fig 1).

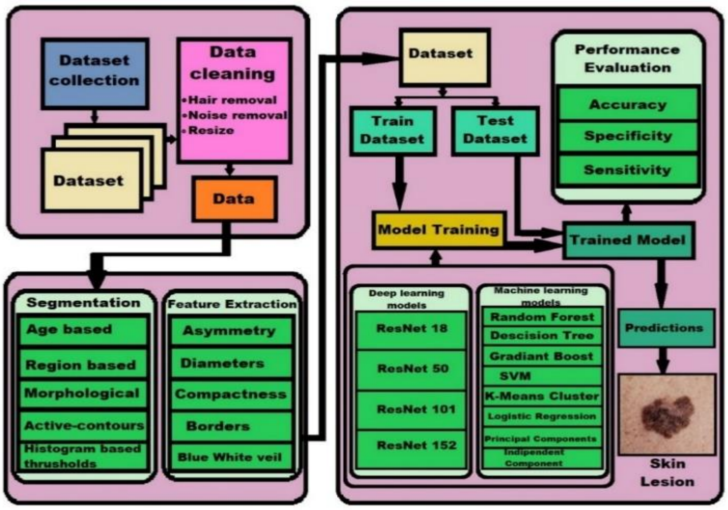


Fig. 1 The System Framework

5. Material and Method

In this section, we will introduce the experimental materials and pre-process method, then analyse the framework of our method in detail.

5.1 Materials

5.1.1 PH^2 Dataset

For melanoma diagnosis in the PH2 data set, A diagnostic study was performed with the machine learning algorithms. A group of researchers from the Technical Universities of Porto and Lisbon established this data set in the dermatology service of Pedro Hispano Hospital. The PH^2 dataset contains 700 dermoscopy images at 720x560 resolution.

In the PH^2 dataset, available 250 images are for MELANOMA types, 230 images for NEVAS images, and 220 images are for seborrheic keratosis. Some examples of these are given in the fig.

A virulent skin imaging process known as Dermoscopy can improve the clarity of the spots by capturing enlightened and larger images of skin lesions disease [8]. The PH^2 database was created in collaboration with Porto University, Technical University, Lisbon, and Hospital Pedro Hispano of Matosinhos.

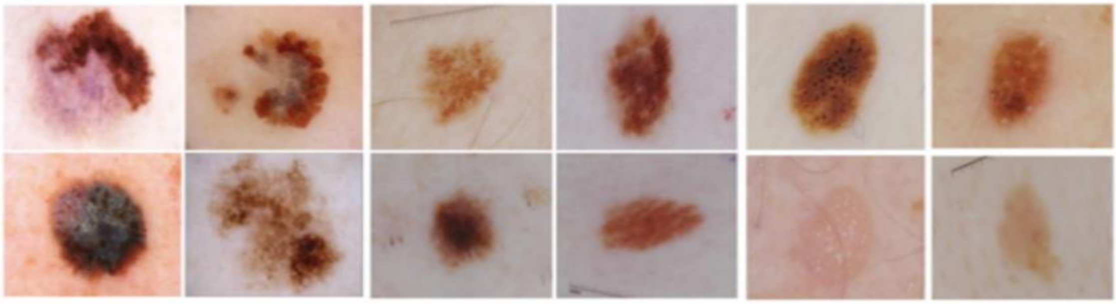
We have identified 105,700 kinds of literature sources [9]. We have increased these sources with 4953 records (e.g. fig. 2). Then we removed the duplicate records and the number of records remaining was 97,599. After that, we applied the inclusion criteria and identified 702 pull-text articles. Consequently, 52 articles using machine learning methods and 43 articles based on deep learning are selected by us [7]. Then we further analyze those selected articles and discuss the result of our study.

Then we listed the selected models which scored based on several tests.

Fig. 2 Some Typical samples show Melanoma, Nevus and SK in Skin Lesion dermoscopic images

5.1.2 ISIC Dataset

Various training images were identified from the international skin imaging collaboration (ISIC) 2016 dataset [8]. This was referred to in the 2016 ISIC-ISBI challenge where every participant has to produce and submit results based on a separate dataset (350 total images) [9]. A training data of about 1950 images, a separate validation dataset of about 180 images, and a blind held-out test dataset of 554 images were provided by this challenge. The training dataset divided into three parts contains 384, 286 and 1269 dermoscopic images for melanoma, seborrheic keratosis, and Nevus.
Various training images were identified from the international skin imaging collaboration (ISIC) 2018 dataset (e.g. fig. 3). The International Skin Imaging Collaboration (ISIC) 2018 dataset, which is also known as the HAM10000 ("Human Against Machine with 10,000 training images") dataset [10].



Melanoma **Seborrheic Keratosis** **Nevus**

Fig. 3. The Skin Lesion Datasets

5.2 Machine Learning Methods

Machine Learning is subsequent to artificial intelligence or AI and computer science which depends upon the use of analysing data and algorithm and follow the way of learning humans by gradually improving the accuracy of the model.

5.2.1 Support Vector Machine (SVM)

It's a Non-parametric classifier that has no preliminary information available regarding its distribution. Training sets consist of paired input and output decision functions are obtained which are used to identify the input variables within the new test and data set through these pairs [15]. The new transformed dimension is being investigated within the separator plane of the maximum margin (e.g. fig. 4).

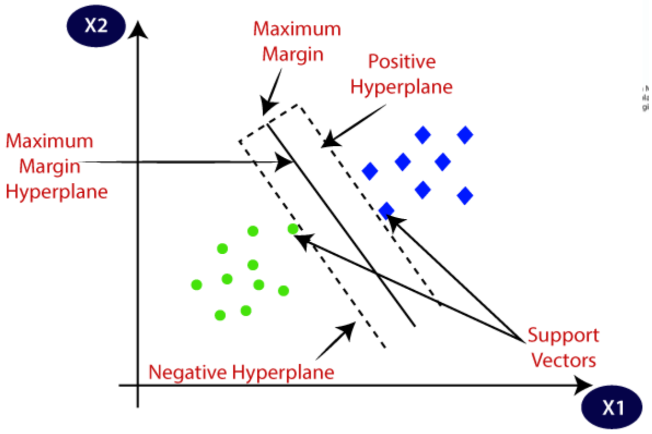


Fig. 4 Working of the SVM model

5.2.2 Decision Tree (DT)

A classifier algorithm in the structure of the tree is known as Decision Tree (DT). As these are very simple, these methods are mostly used by moving the inductive logic in the programming environment 9 (e.g. fig 5). DTs work on the basis of discrete values parameters. The basic inductive philosophy on which the algorithms of decision tree are based is that a good decision tree is constructed with much smaller learning characteristics [16].

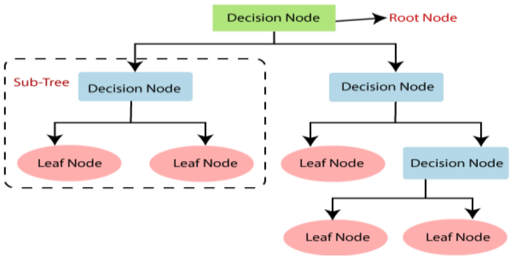


Fig. 5 Working of the DT model

5.2.3 Random Forest

A well-known machine learning algorithm that belongs to a supervised learning technique is known as Random Forest. Problems in machine learning such as classification and regression can be solved using this algorithm. A classifier, known as Random Forest is made up of multiple decision tree based on different subsets of the proposed dataset [20]. It is also used to improve the predictive accuracy of that dataset by taking the average. As soon as the number of trees in a forest increases, the accuracy also increased (e.g. fig. 6). This helps to prevent the problems of overfitting.

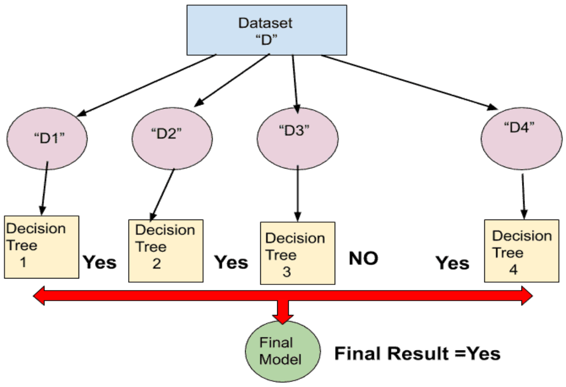


Fig. 6 Working of RF model

5.2.4 Logistic regression

It is one of the popular machine learning algorithms known as Logistic regression. It comes within the superintend learning techniques predicting the categorical dependent variable with the aid of a given set of independent variables is used Logistic regression has many similarities with linear regression except their uses. This is used for solving classification problems instead of regression problems which are solved by linear regression (e.g. fig 7).

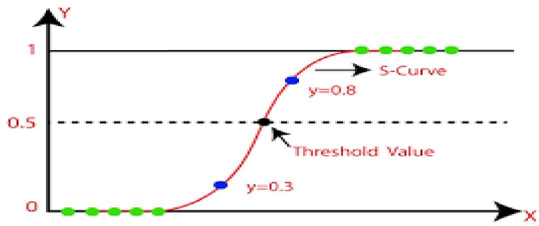


Fig. 7. Working of LR model

5.2.5 K-Clustering

Clustering is a technology system to catch classes of observations where a specific dataset is provided, that contribute identical features and where a data analysis technique is used to get a clue about the structure of the data [12] (e.g. fig 8). It is resolute and interpreted the data which is one of the important features of this unsupervised clustering it also reforms compact clustering and can work on numerical data but it has limitations also which highly depend on the original data and it is difficult to forecast the number of clusters [27].

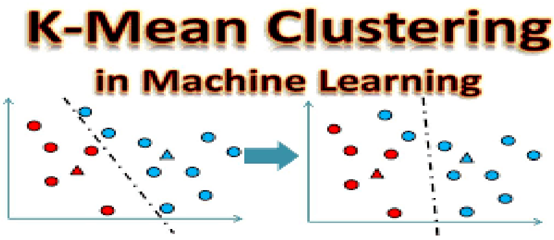


Fig. 8. Working of K-clustering model

5.2.6 Principal Component Analysis

PCA is a famous non-superintended algorithm that has been used in different ways like analysis, compression, de-noising, reducing the dimension of data, etc. It helps to eliminate similar data in the line of comparison that does not need a bit to make data decisions. It is an unsupervised machine learning algorithm that is used to reduce the dimension of a dataset although it collects the information as much as possible. Many techniques have been discovered for this process, but principal component analysis is the most widely used. Its main motive is to reduce the size of a dataset [13] (e.g. fig. 9). It has some limitations which are; It is non-parametric; no data knowledge can be incorporated. The other one is that PCA data reduction often causes a loss of information.

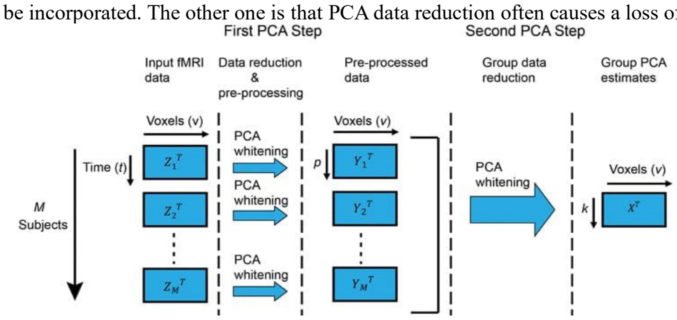


Fig. 9. Working of Principal component analysis

5.2.7 Independent Component Analysis:

It is the technique of which is used to detect factors that are hidden existed in datasets of random variables, signals, or measurements. It is an alternative technique to Principal Component Analysis that helps to separate multivariance signals that are assumed to be non-Gaussian in nature, and independent of each other. It is a non-parametric technique, that does not require presumptions about the spread of the data [22]. It is an unlooked-after learning technique, which means that it can be applied to data without the need for labeled examples.

It can be used in future extraction and it can also identify other tasks like specification and classification (e.g. fig 10). But it has some disadvantages where it cannot identify the mixed linear data [14],[18]. Although these techniques cannot be used for practical problems. It can suffer from Random Forest issues the means it is always not possible to find the solution.

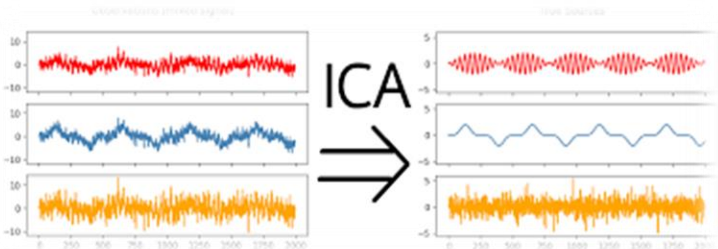


Fig. 10. Working of independent component analysis

5.2.8 Gradient Boosting

Boosting is a machine learning technique that is used to build strong classifiers resembling various weak classifiers. It identifies the errors in the primary model. then a secondary model is built from that, and further, a third model is applied in this process. In this process, we can get error-free data from the model. Gradient boosting is one of the forward ensemble machine learning model. It is mainly used for classification [23]. It is a looked-after machine learning algorithm that is based on a predictive method. It is based on three elements which are the Loss function, Weak learners, and Additive model, this machine learning technique is based on the next model intuitively. It can use several ranges of basic learners, where it is naturally more robust and less sensitive than other models (e.g. fig. 11).

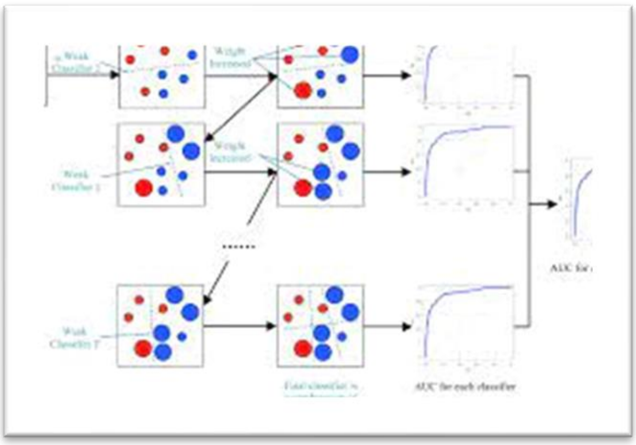


Fig. 11. Working of Gradient Boosting

To examine the border and color of skin lesions, the rule of (ABCD) asymmetry, border, colour, and diameter was used by the authors. This feature was classified by them using a Multimeter Perception Network (MLP), which is based on backpropagation training. To improve the image and pick up hair (e.g.[19],[20]) A Gabor filter and geodesic active contours are used. Then the features are extracted by using the ABCD scoring method.

A skin lesion method was proposed by Roberts et al. on the ensemble model for feature tactic. Fractal methods of multispectral skin lesion analysis was proposed by Przystalski et al. A melanoma detection system using a smartphone was introduced by them. A smartphone camera is used for acquiring the images.

A feature extraction method using local binary pattern (LBP), wavelet transform and curvelet transform has been proposed by Adjed et al. Finally, SVM is used for the classification of the extracted feature. Particle Swarm Optimization (PSO) for skin lesion feature optimization has been enhanced by Tan et al. Two PSO models for discriminative feature selection have been modified by two authors, such as: A global search by combining lesion features and an in-depth local search by differentiating into selected areas has been performed by first one.

The structural co-occurrence Matrix of frequencies extracted from dermoscopic images has been utilized by the authors to classify skin lesions. Skin lesions by detecting skin cells using Fourier transform infrared have been classified by Penaranda et al. Combining these results, a study was conducted and used for the perturbations and the results were influenced to determine the right effects.

5.3 Deep Learning Methods

This process of Deep Learning is used to perform maximum computations on a huge some of data. The term Deep Learning has been taken from machine learning modules that use neural networks with more than three layers for more accurate output. Complex picture patterns, text, sound, and other kinds of audio-visual data can be recognized with the help of deep learning. Deep Learning methods are also used for the automation of different tasks which require human intelligence such as describing any images or transcription of audio files into a text document.

5.3.1 RESNet 101

Generally, in a deep convolutional neural network, many layers are trained for the task at once. The neural network has many features at the end of its layers (e.g. [21],[25]). ResNet deep learning does shortcut connections by directly connecting the input of the nth layer to the (n+x)th layer. So, it has been proved that ResNet has solved this training problem in the recognition task. ResNet101 is a variant of ResNet.

In a residual blocks neural network, each layer is related to the next layer and directly into the next layer (e.g. fig 12). We need to focus on architecture first in Resnet 101.

ResNet-101 is a 101 layers deep convolutional neural network. A ResNet 101 is very much larger and it is also slower to train where It usually depends on the dataset which must be the smallest simpler model managed with the complexity [27].

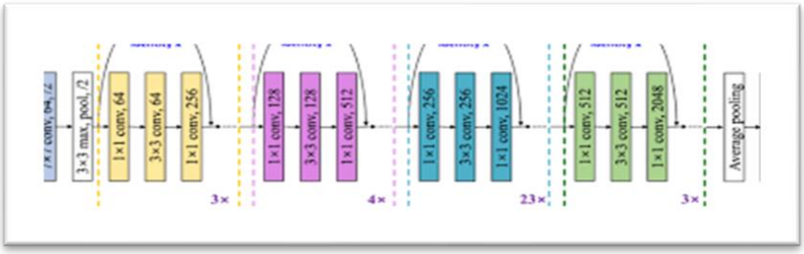


Fig. 12. Working of RESNet 101 Structure

ResNet 101 consists of 101 convolutional layer which is made of 33 blocks of layer and 29 square of these layers which is connected to the previous layer directly. This residual network is trained in such a way that it includes 1000 object classes [29]. There are also includes 72 parameters. The biggest advantage of the Resnet 101 is the optimization of the input and the desired property. This optimization reduces the parameter of the network [32].

5.3.2 RESNet 50

Resnet 50 is a neural network. In Resnet 50 there are too many convolutional layers attached one by one. The input image is used in the first layer as if we can also see there are some predefined things. If we calculate all the layers, we get a total of 50 layers. The Max pooling layer is also used here [26]. There are 3 kinds of layers which are the convolution layer, rallied layer, and pooling layer There are 48 convolutional layers and two others are the average pooling layer and max pooling layer. (e.g. fig. 13)

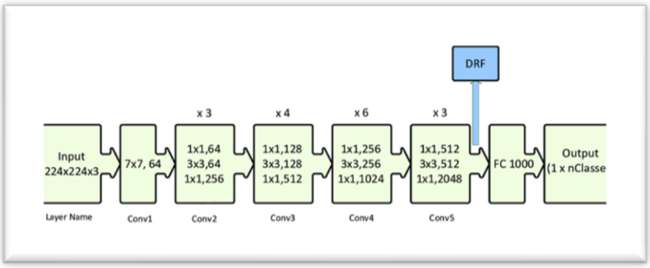


Fig. 13. Working of RESNet 50 model

5.3.3 RESNET 18

In Resnet 18, there are 18 layers total in number and they are connected to each other. By configuring the number of blocks and many layers we can deep layer Resnet network 152.
The architecture of Resnet 18 is really easy to understand. It is a 72 architecture where the convolutional layers function properly. It is the main advantage of Resnet 18 [30]. And also, the primary pooling layers are not counted that’s why this architecture is the simplest. The architecture of Resnet 18 is given below (e.g. fig 14).

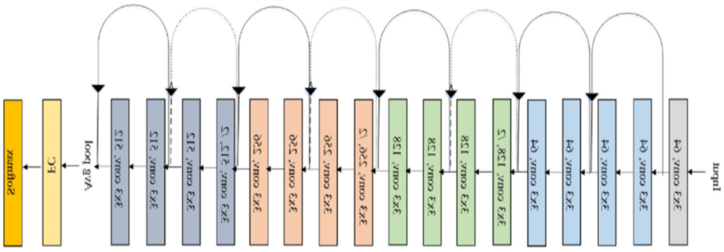


Fig. 14. Working of RESNet18 model

5.3.4 RESNET 152

Resnet152 is used in our project basically used for image classification. As different visual recognition tasks have also greatly benefited from very deep models. This residual Learning network is used to overcome some recognition problems more than other neural networks.
This residual model has 152 layers. But it is slightly different from other ResNet models. Cause it has blocks that skip connection blocks. And also, always allows an easy way to gradient to the early layer [31]. This model requires down-sampling. It has 3x3 convolutional layers (e.g. fig 15). That's why it helps to train deeper models.

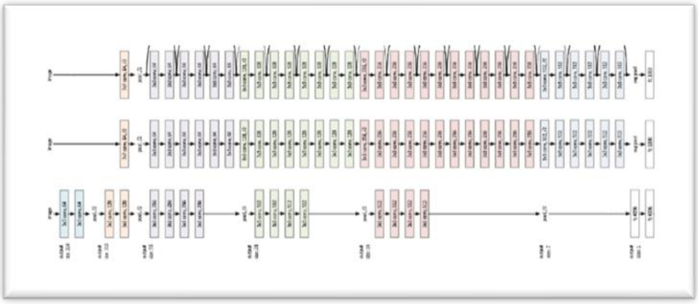


Fig. 15. Working of RESNet 152 model

6. The Performance Evaluation which is Accepted Commonly

Here we focus on the study. The most general way for comparing algorithms is classification performance without focusing on a class. The empirical measures are used mostly and the accuracy cannot be distinguished between the number of accurate tables and the different types of class levels.

TP= True Positives: No. of actual examples predicted which are actually positive.
FP= False Positive: No. of actual examples which are predicted positively but are actually negative.
TN= True Negative: No. of actual examples which are predicted negative and also negative actually.
FN= False Negative: No. of actual examples which are predicted negative but are actually positive.
ACCURACY: Total number of records which are correctly classified by the classifier is referred to as accuracy. Accuracy can also be defined as the percentage of test set tuples that are classified accurately by the model.

$$\boldsymbol{accuracy} = \frac{TP + TN}{TP + FP + FN + TN} x100\%$$

SENSITIVITY: The true positive rate that includes the proportion of the positive tuples which are correctly classified is known as the sensitivity.

$$\boldsymbol{sensitivity} = \frac{TP}{TP + FN} x100\%$$

SPECIFICITY: The rate by virtue of which a Test or a diagnostic method sets a standard diagnosis for a person who is not affected is known as Specificity.

$$\boldsymbol{specificity} = \frac{TN}{TN + FP} x100\%$$

ROC CURVE: ROC stands on the Receiver Operating Characteristics curve which displays both the specificity and sensitivity of the test. The comparison between TPR (True Positive Rate) and FPR (False Positive Rate) is known as the ROC curve.
i.e., TPR = TP (TP+FN) and FPR = FP (FP+TN).

$$AUC = \int_0^1 t_{pr}(f_{pr})df_{pr} = P(X1 > X0)$$

Where t_{pr} is the true positive rate, f_{pr} is the false positive rate, and X0 and X1 are the confidence scores for a negative and positive instance, respectively.

7. CONVOLUTION NEURAL NETWORK Architecture

There are various methods using CNN have been proposed to solve this kind of problem. To solve these problems a dataset is chosen where we use CNN architecture. A training input size of about 1510 images has been used to perform this experiment (e.g. [35],[36]). The image size taken as input by our proposed CNN architecture is about 224 x 224 pixels. However, pre-processing is also required before training the model [24]. The CNN architecture is made of 9 layers.

There 3 convolution layers of filter size 3 x 3 are used with the Relu activation function (e.g. fig. 16). A feature representation of the input intensity patch is aimed to be learned by the convolution layers, as well as this is also consisting of a combination linear and non-linear operation, therefore, convolution and activation function.

The problems like increasing overfitting can be solved by obtaining more training data. But this solution is impractical in medical imaging due to the deficiency of labeled data [19]. To solve this problem, we regularize with dropout and which is the newest technique of regularization. By observing the final output of this network, the probabilities of a lesion can be assumed [24]. It may be either malignant or benign.

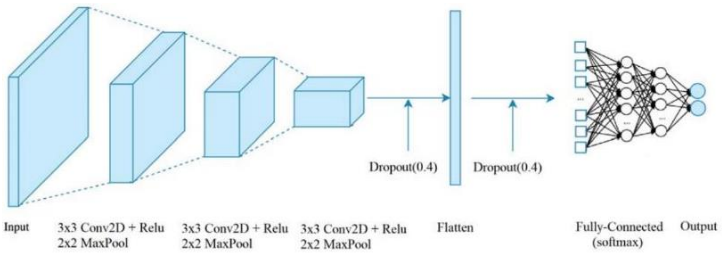


Fig. 16. Working of CNN model

A skin lesion classification method using CNN has been proposed by Kawahara et al. This CNN which is modified by trading can classify various resolution images. A novel CNN for skin lesion classification and segmentation has been proposed by YU et al [26]. A skin lesion segmentation system has been proposed by Yuan et al. By leveraging CNN consisting of 19 layers. They utilized Jaccard distance as a loss function which substitute the traditional loss function. A skin lesion detection system has been proposed by Sultana et al. using deep residual learning along with a regularized framework (Madooei et al., 2012). To classify skin cancer a depth-wise separable residual deep convolutional network has been proposed by Sarkar et al. The contrast-limited adaptive histogram equalization (CLAHE) over the discrete wavelet transform (DWT) algorithm succeeded the non-local means filter (Theo et al., 2017). Now, the proposed CNN can check and differentiate seven points melanoma checklist criteria more accurately.

8. Proposed Methodology

- Step 1: Prepare the Image Data Set.
- Step 2: Pre-process the data.
- Step 3: Import the library files.
- Step 4: Load the data set for classification.
- Step 5: Divide the data set into a two-part training dataset and test data set.
- Step 6: Use the specific model CNN-based deep learning and machine learning for training purposes.
- Step 7: Check the model accuracy by testing the data set.
- Step 8: Prevalence the study by using results.

9. Experiment Methodology

The experiment in this project work was conducted using PH2 and ISIC (International Skin Imaging Collaboration) Dataset, it holds more than 26000 images of melanoma, nevus, and Seraborric Keratosis. We use for our work with only 800 numerical skin lesion images, from these 600 images will be used as a training set and the rest of them are test sets. CNN model is trained by 650 images by the size 224x224 using different types of machine learning and deep learning modules. It is shown that the CNN has the highest performance over all others, all through machine learning and deep learning techniques has a few advantages for detection of the skin lesion whereas the CNN cannot. In this matter, a result aggregation of the different methods is used in the performance of the melanoma detection system. In this paper we can use the many different types of machine learning and deep learning techniques based on CNN and their accuracy is shown below (e.g. table II - table VII). This experiment was conducted by Google Collaboratory with Epoch 30 and different types of backend functions.

Table II: Melanoma Detection Using Deep Learning

Models	**Accuracy**	**Sensitivity (SPE)**	**Specificity (SEN)**	**AUC**
ResNet 18	85.02%	79.78%	73.58%	0.874 (87.4%)
ResNet 50	87.96%	86.62%	88.17%	0.881 (88.1%)
ResNet **101**	**97.73%**	**98.25%**	**95.17%**	**0.982 (98.2%)**
ResNet 152	89.26%	88.21%	91.27%	0.903 (90.3%)

Table III: Seborrheic Keratosis Detection Using Deep Learning

Models	**Accuracy**	**Sensitivity (SPE)**	**Specificity (SEN)**	**AUC**
ResNet 18	71.02%	69.58%	72.98%	0.722 (72.2%)
ResNet 50	85.96%	83.68%	87.20%	0.861 (86.1%)

ResNet 101	78.23%	82.20%	77.36%	0.790 (79.0%)
ResNet 152	**98.85%**	**99.04%**	**96.02%**	**0.989 (98.9%)**

Table IV: Nevus Detection Using Deep Learning

Models	**Accuracy**	**Sensitivity (SPE)**	**Specificity (SEN)**	**AUC**
ResNet 18	74.56%	73.45%	76.65%	0.758 (75.8%)
ResNet 50	87.63%	85.25%	88.14%	0.886 (88.6%)
ResNet 101	**96.93%**	**97.45%**	**95.62%**	**0.972 (97.2%)**
ResNet 152	86.25%	88.04%	85.02%	0.863 (86.3%)

Table V: Melanoma Detection Using Machine Learning

Models	**Accuracy**	**Sensitivity (SPE)**	**Specificity (SEN)**	**AUC**
Random Forest Algorithm	78.69%	80.25%	75.24%	0.793(79.3%)
Decision Tree Algorithm	84.58%	87.82%	83.67%	0.852(85.2%)
Logistic Regression Algorithm	73.8.41%	72.63%	74.86%	0.749(74.9%)
Support Vector Machine Algorithm	78.96%	81.21%	75.83%	0.795(79.9%)
Gradient boost	**97.85%**	**97.19%**	**98.52%**	**0.979(97.9%)**
K-Means Clustering algorithm.	75.62%	74.46%	78.82%	0.768(76.8%)
Principal Component Analysis.	55.41%	58.49%	55.02%	0.563(56.3%)
Independent Component Analysis.	85.69%	87.62%	82.68%	0.861(86.1%)

Table VI: Seborrheic Keratosis Detection Using Deep Learning

Models	**Accuracy**	**Sensitivity (SPE)**	**Specificity (SEN)**	**AUC**
Random Forest Algorithm	71.02%	69.58%	72.98%	0.772 (77.2%)
Decision Tree Algorithm	85.96%	83.68%	87.20%	0.861 (86.1%)
Logistic Regression Algorithm	**96.93%**	**95.45%**	**97.62%**	**0.973 (97.3%)**
Support Vector Machine Algorithm	64.56%	66.45%	63.56%	0.643 (64.3%)
Gradient boost	93.25%	91.15%	95.32%	0.939(93.9%)
K-Means Clustering algorithm.	89.25%	91.02%	88.30%	0.893(89.3%)
Principal Component Analysis.	78.65%	77.01%	80.32%	0.792(79.2%)
Independent Component Analysis.	92.10%	90.23%	93.65%	0.924(92.4%)

Table VII: Nevus Detection Using Deep Learning

Models	Accuracy	Sensitivity (SPE)	Specificity (SEN)	AUC
Random Forest Algorithm	68.25%	69.23%	66.25%	0.696(69.6%)
Decision Tree Algorithm	78.96%	76.21%	80.49%	0.793(79.3%)
Logistic Regression Algorithm	86.47%	83.59%	89.28%	0.876(87.6%)
Support Vector Machine Algorithm	**97.98%**	**98.63%**	**99.01%**	**0.985(98.5%)**
Gradient boost	80.26%	82.29%	77.19%	0.809(80.9%)
K-Means Clustering algorithm.	72.39%	69.37%	75.49%	0.734(73.4%)
Principal Component Analysis.	54.29%	56.62%	53.24%	0.558(55.8%)
Independent Component Analysis.	72.68%	73.84%	72.56%	0.739(73.9%)

10. Result Analysis

Based on the result of our machine learning and deep learning methods done with ResNet 18,50,101,152 and machine learning models like Random Forest, Decision Tree, Support Vector Machine (SVM), Gradient boost, K-Means Clustering, Principal Component Analysis, Independent Component Analysis. We can compare the Accuracy, and AUC of different deep learning and machine learning modules based on CNN. From the accuracy table, we can conclude that in the case of machine learning for Melanoma detection, we got our best accuracy at Logistic Regression, for seborrheic keratosis highest accuracy was obtained at Support Vector Machine (SVM), and for Nevus we get highest accuracy in Gradient boost. Again, in case of CNN base deep learning algorithms highest accuracy for melanoma and seborrheic keratosis detection was obtained in ResNet 101 and for Nevus we get highest accuracy in ResNet 152.

Through our project work, we have classified several types of skin lesion diseases like Melanoma, Seborrheic Keratosis, Nevus through Deep Learning and Machine Learning modules.

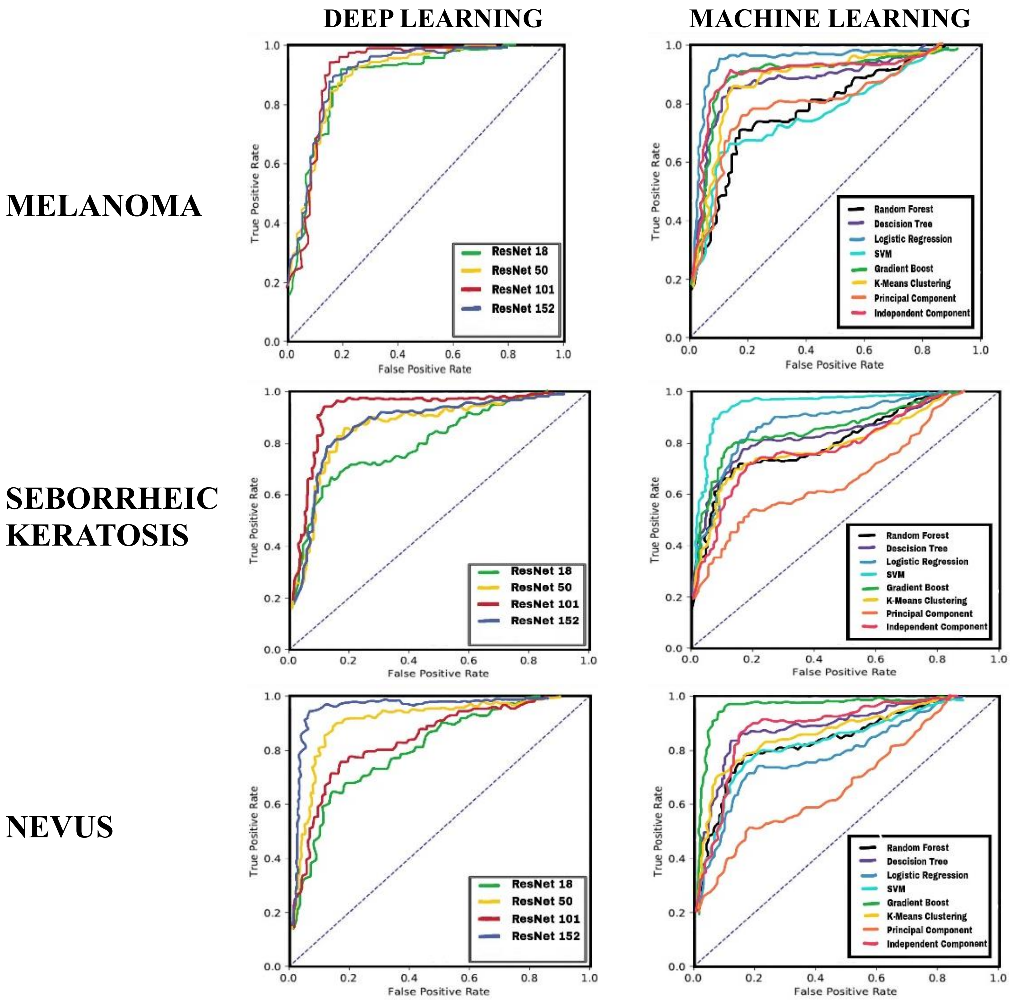


Fig. 17. AUC graph of different types of Deep Learning and Machine Learning models

11. Conclusion

After completion of our project work, we can hereby conclude that Skin Lesion diseases like Melanoma, Seborrheic Keratosis, Nevus Can be classified with the help of CNN-based Deep Learning and several Machine Learning modules. We get different accuracy from different types of skin lesions while classifying with the model. Finally, we observed the Deep Learning modules based on CNN are more accurate.

12. Acknowledgement

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13. References

[1] N. C. F. Codella et al., "Skin lesion analysis toward melanoma detection: A challenge at the international symposium on biomedical imaging (ISBI), hosted by the international skin imaging collaboration (ISIC)," (2017)[Online]. Available: https://arxiv.org/abs/1710.05006

[2] Y. LeCun, Y. Bengio, and G. Hinton, "Deep learning," *Nature*, Vol. 521, pp. 436–444, 2015.

[3] N. Hameed, A. Ruskin, K. A. Hassan, and M. A. Hossain, "A comprehensive survey on image-based computer aided diagnosis systems for skin cancer," *2016 10th International Conference on Software, Knowledge,Information Management & Applications (SKIMA)*, Vol. 8, pp. 254-259, 2016.

[4] A. Mahbod, R. Ecker, and I. Ellinger, "Skin Lesion Classification Using Hybrid Deep Neural Networks,", 2017, .arXiv:1702.08434v1 [cs.CV].

[5] S. Karimkhani, C. Green, A.C. Nijsten, T. Weinstock, M.A. Dellavalle, R.P. Naghavi, M. Fitzmaurice, "The global burden of melanoma: Results from the Global Burden of Disease Study 2015," *Br. J. Dermatol*, Vol. 177, pp.134–140, 2015.

[6] V. Braun, R.P. Rabinovitz, H.S. Oliviero, M. Kopf, A.W. Saurat, J.-H., "Dermoscopy of pigmented skin lesions," *J. Am. Acad. Dermatol,* Vol. 52, pp.109–121, 2005.

[7] S. Rajpara, S.M. Botello, A.P. Townend, J. Ormerod, "A.D. Systematic review of dermoscopy and digital dermoscopy/artificial intelligence for the diagnosis of skin lesion," *Br. J. Dermatol,* Vol. 161, pp.591–604, 2009.

[8] X. Gutman, D. Codella, N.C.F. Emre, C. Brian, H. Michael, M. Nabin, M. Allan, H., "Skin Lesion Analysis toward Melanoma Detection: A Challenge at the International Symposium on Biomedical Imaging (ISBI) 2016," *International Skin Imaging Collaboration (ISIC),*2016*,* arXiv 2016, arXiv:1605.01397.

[9] N. Gutman, D. Celebi, M.E. Helba, D. Marchetti, M.A. Dusza, S. Kalloo, A. Liopyris, K. Mishra, N. Kittler, H. et al., "Skin Lesion Analysis : A Challenge at the 2017 International Symposium on Biomedical Imaging(ISBI)," *International Skin Imaging Collaboration (ISIC),* 2017,arXiv 2017, arXiv:1710.05006.

[10] C. Tsch, P. Rosendahl, C. Kittler, H., "The HAM10000 dataset, a large collection of multi-sources dermatoscopic images of common pigmented skin lesions," *Sci. Data* , Vol. 5, pp.180-161, 2018.

[11] F. Abuzaghleh, O. Barkana, B.D. Faezipour, M. Noninvasive, "Real-Time Automated Skin Lesion Analysis System For Early Detection and Prevention," *IEEE J. Transl. Eng. Health Med*, Vol. 3, pp.1–12, 2015.

[12] D. Pelleg, A. Moore, "X-means: Extending K-means with Efficient Estimation of the Number of Clusters," *ICML '00 Proceedings of the Seventeenth International Conference on Machine Learning*, pp. 727-734, 2000.

[13] K. Potdar, R. Kinnerkar, "A Comparative Study of Machine Algorithms applied to Predictive Breast Cancer Data," *International Journal of Science & Research*, Vol. 5, Issue 9, pp. 1550-1553, 2016.

[14] S. Ray, "A Quick Review of Machine Learning Algorithms," *International Conference on Machine Learning, Big Data, Cloud and Parallel Computing*, Vol. 6, Issue 10, pp. 523-529, 2019.

[15] V. De Vita, G. L. Di Leo, G. Fabbrocini, C. Liguori, A. Paolillo, and P. Sommella, "Statistical techniques applied to the auto-matic diagnosis of dermoscopic images," *ACTA IMEKO*, vol.1, no. 1, pp. 7–18, 2012.

[16] G. Surowka and K. Grzesiak-Kopec, "Different learning paradigms for the classification of melanoid skin lesions using wavelets. In,"*29th Annual International Conference of the IEEE Engineering in Medicine and Biology Society (EMBS '07)*, pp. 3136–3139, 2007.

[17] S. Kaymak, P. Esmaili, A. Serener, "Deep Learning for Two-Step Classification of Malignant Pigmented Skin Lesions," *Neural Networks and Applications*, pp. 102-103, 2018.

[18] A. Doaa, M. Shoieb, E. Sherin, M. Youssef, Walid M. Aly "Skin Diagnosis Using Deep Learning," *Journal of Image and Graphics Computer-Aided Model,* Vol.8 ,pp. 185-174, 2016.

[19] R. Ramadan, S. Aly, and M. Abdel, Aty. Sohag, "An Efficient Skin Lesion Segmentation Using Deep Fully Convolutional Neural Network with Gradient Skin Images," *Journal of Science*, Vol. 8, pp. 145-149, 2013.

[20] G. Yosipovitch, K. C. Mills, MD Leigh, A. Nattkemper, MS Ashley Feneran, Hong Liang Tey, Brett M. Lowenthal, D. J. Pearce, P. M. Williford, O. P. Sangueza, R. B. D'Agostino, "Skin Cancer Results of a Large Clinicopathologic Study," *Pain and Itch With Depth of Invasion and Inflammatory Cell Constitution,* Vol. 7, pp. 145-196, 2023.

[21] P. M. Burlina, N. J. Joshi, E. Ng, S. D. Billings, A. W. Rebman, J. N. Aucott, "Automated detection of erythema migrans and other confounding SKIN lesions via deep learning," *Computers in Biology and Medicine,* Vol.9, pp. 85-89, 2018.

[22] U. Dorj, K. Lee, J. Choi, Malrey Lee, “The skin cancer classification using deep convolutional neural network”, *Springer Science+Business Media,* Vol.1, pp.369 375, 2015.

[23] D. Bisla, A. Choromanska, J. A. Stein, D. Polsky, R. Berman, “SKIN LESION SEGMENTATION AND CLASSIFICATION WITH DEEP LEARNING SYSTEM,” *New York University School of Medicine ,* Vol. 6, pp. 548-559, 2019.

[24] R. Francese1, M. Frasca1, M. Risi, G. Tortora, “A mobile augmented reality application for supporting real-time skin lesion analysis based on deep learning,” *Journal of Real-Time Image Processing,* Vol.3, pp.1235-1242, 2021.

[25] Z. Qina, Z. Liub, P. Zhua, Y. Xuea, “A GAN-based image synthesis method for skin lesion classification”, *ELSEVIER ,* Vol. 7, pp. 456-480, 2020.

[26] A. Masood, A. Ali, Al-Jumaily, “Computer Aided Diagnostic Support System for Skin Cancer: A Review of Techniques and Algorithms,” *International Journal of Biomedical Imaging, Vol. 10, pp. 756-765, 2013.*

[27] https://www.javatpoint.com/k-means-clustering-algorithm-in-machine-learning

[28] N. Codella, J. Cai, M. Abedini, R. Garnavi, A. Halpern, J. R. Smith, “ Deep Learning, Sparse Coding, and SVM for Melanoma Recognition in Dermoscopy Images,” *Springer International Publishing Switzerland,* Vol. 19, pp. 1426-1430, 2015.

[29] Le. Thao, N. Hong, “Automatic skin lesion analysis towards melanoma detection,” *Asia Pacific Symposium on Intelligent and Evolutionary Systems,* Vol.41, pp. 523-530, 2017.

[30] A. Madooei, M. S. Drew, M. Sadeghi, M. Stella, “Intrinsic Melanin and Hemoglobin Colour Components for Skin Lesion Malignancy Detection,” *Atkins School of Computing Science Simon Fraser University,* Vol. 25, pp. 10-17, 2012.

[31] M. E. Celebi, S. Member and Azaria Zornberg, “Automated Quantification of Clinically Significant Colors in Dermoscopy Images and Its Application,” *IEEE SYSTEMS JOURNAL,* IEEE*,* Vol. 5, pp.896-900,2014.

[32] J. Zhang, Y. Xie, Yong Xia , C. Shen, “Attention Residual Learning for Skin Lesion Classification,” *IEEE NPSS*, Vol. 6, pp.521-530, 2019.

[33] C. W. Hsu, C. C. Chang, C. J. Lin, “A practical guide to support vector classification,” 2003.

[34] U. Fidan, İ. Sarı and R. K. Kumrular, ""lassification of skin lesions using ANN,” *Medical Technologies National Congress (TIPTEKNO) 2016*, pp. 1-4, 2016.

[35] S. Jain, N. Pise, “Computer aided skin cancer detection using image processing,” *Procedia Computer Science*, vol. 48, pp. 735-740, 2015.

[36] G. Arroyo, J. L., G. Zapirain, B.,“Segmentation of skin lesions based on fuzzy classification of pixels and histogram thresholding,*” Neural Network,* 2018.

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