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Machine Learning in Medical Imaging for Early Detection of Skin Diseases.

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Abstract: Dermatology is a medical field that treats skin health and diseases. These skin diseases are perilous and often transmittable but can be cured or reversed with higher degree if detected at an early stage. Early detection and treatment can correct most skin disorders. Diagnosis of these diseases requires a sophisticated of proficiency due to the variety of their illustration aspects. As manual conclusion are often skewed and hardly reproducible, to achieve a more intent and undependable diagnosis, a computer aided diagnostic system should be considered. This work is to provide a comparative view of advancements the works as a robust literature of with techniques, methodology, experimented results and dataset done in medical science using medical images to predict diseases with early detection and higher accuracy .

Keywords: Dermatoscopic, Imaging modality, feature map, superficial learning, shallow learning, deep learning, transfer learning.

I. INTRODUCTION

Disability-adjusted life years (DALYs) is 18th leading effect of mortality in year 2013 among 188 countries. In 2013, there was a constant increase of approximately 42.7% of patients and at present and a higher vision to learn more about traumatism in their medicine. About 5 million people are facing the problem of skin cancer and 20% of persons in U.S. is reported to develop in lifetime [1][2].

Early detection and treatment can be prominent in cure or reverse with higher degree to curtail mortality. A computer aided diagnostic system that can achieve a more intent and undependable diagnosis with clinical accuracy available in literature are reviewed and compared or explored for techniques, methodology, experimented results and dataset.

Skin conditions contributed 1.79%ztozthezglobalzbur denzofzdiseasezmeasuredzinzDALYszfromz306zdiseasesza ndzinjurieszinz2013. Individual skin diseases varied in si ze from 0.38%of total burden for dermatitis (atopic, cont act,zandzseborrheiczdermatitis), 0.29% for acne vulgaris, 0.19% for psoriasis, 0.19% for urticaria, 0.16%for viral s kin diseases, 0.15% for fungal skin diseases, 0.07%for s cabies, 0.06%for malignant skin melanoma, 0.05% for pyoderma, 0.04%for cellulitis, 0.03%for keratinocyte carcinoma, 0.03%for decubitus ulcer, and 0 .01% for alopecia areata.zAllzotherzskinzandzsubcutaneou szdiseaseszcomposedz0.12% of total DALYs.

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II. RELATED WORK

The assessment and innovation of the computing techniques of diagnostic medical experts are for the control of classification system of essential importance plays in the meadow of medical diagnosis that provides preventive step by an early detection[3]. Various models in the literature put forward and illustrate considerable buckle in the early detection of skin disorder in **Table 3: Literature and performance statistics.**

III. METHODOLOGY

Strategy implementation refers to the carrying out of the procedures, modules and strategies, so as to complete the overall work as the solution or architecture for the problem statement. It depicts the followed strategy into the steps **AND** actions of the functioning of system to achieve the objectives. Architectures reviewed in most of the potential works registered as a robust work in literature is shown in the following figure "Fig. 1" .

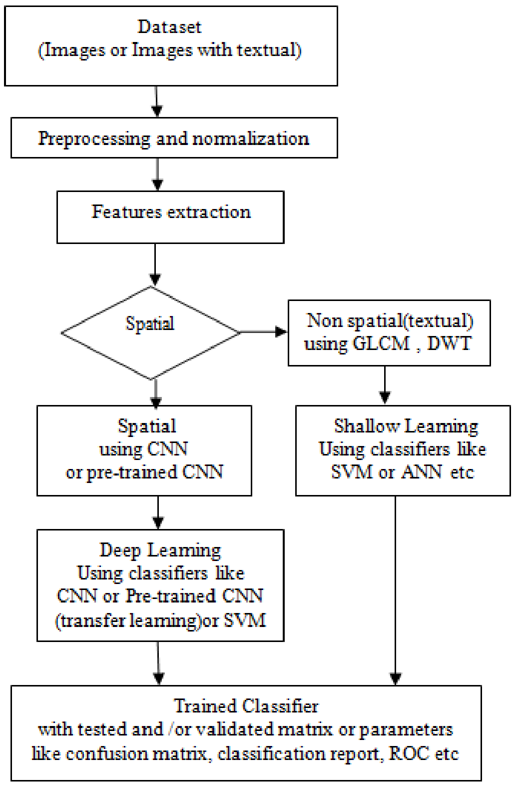

Fig. 1: Architecture(s) of compared works reviewed in literature.

Pre-processing or augmentation means a set of operations on input images at the first level of notion on given images. The aspire of pre-processing is an enhancement of the given image that suppresses superfluous noises or improving some image features imperative for additional or next level processing. This also includes balancing of number of samples or images used to train a model in each class that is some augmentations for some images.

Feature extraction is a technique of extracting illustration substance of images for further referencing or training. Primitive or low level features can be common features, such as extraction of color, texture (textual) etc. Spatial features refers to features which exploits location or spatial information.

Shallow learning performs on the features extracted for developing the prediction model and technically involves one hidden layer. Whereas, deep learning shows the latent to fetch superior representations from the untreated data to develop much enhanced models and technically involve more than one hidden layers.

IV. RESULT

Evaluation of model means to calculate the generality accuracy on unseen data used as future data to be predicted by model. Methods for evaluating a model's performance are discussed as Holdout (or split and validation) and Cross-validation.

Holdout also called "testing" data, is a **holdout** subset (mostly 75 to 25 ratio) gives a concluding estimation of performance of the developed model.

Cross-validation is a procedure that practice partitioning the input dataset into a variable size of training and testing sets. The most familiar cross-validation method is k-fold cross-validation, where the input dataset is divided into k equal size subsets, called folds. The k is a user-defined value, generally with 5 or 10 as its favored magnitude. This is continual k times, such that each time, one of the k subsets is worn as the test set/validation set and the other k-1 subsets are positioned to shape a next training set. The performance estimation is averaged over all k cases to get the final efficiency of the model.

Most of the important matrix used to evaluate performance of trained model in reviewed works, are the confusion matrix, the classification report and the ROC. All of these are listed in **Table 1: Different validation matrix used to validate a trained model and Table 2: Validation parameters used for different validation matrix.**

Table 1: Different validation matrix used to validate a trained model.

S.N.	Validation Matrix
1	Confusion Matrix
2	Classification Report
3	ROC(AUC) plot
4	ROC(AUC) plot with micro and macro average(in case of more than two classes)

The confusion matrix shows all true labels against all predicted labels to calculate TP, FP, TN and FN. It is a performance measurement to test validation of a trained classification model where output can be of binary or multiclass classification. It is a matrix with 4 different combinations of predicted (Positive, Negative) and actual (True, False) values. It is particularly valuable for calculating Recall, Precision, Specificity, Accuracy and significantly AUC-ROC Curve [26].

Classification report is a matrix that displays precision, recall (sensitivity) and f-score. Precision means "How many selected items are relevant?" and calculated as TP/(TP+FP). Higher precision means low value of false positive. Recall means "How many relevant item s are selected?"and calculated as TP/(TP+FN). Higher r ecall means low value of false negative. F-Score (F_1-score or F-measure) represents perfect value of precision and recall. This is calculated as (2*(precision*recall))/ (precision + recall). F-score best at value 1(worst at 0) where precision and recall are perfect.

ROC curve plots True Positive Rate **(** TPR) and False Positive Rate **(**FPR**).** True Positive Rate **(** TPR**)** is calculated as TP/(TP+FN) and False Positive Rate **(**FPR) is calculated as FP/(FP+ TN).

Area under the ROC Curve (AUC) measures the e ntire twodimensional area underneath the entire ROC cur ve from (0,0) to (1,1). Higher value of AUC means higher value of accuracy for prediction of a model. Further micr oaverage and macroaverage ROC can be expressed in a m ulticlass classification [27].

Table 2: Validation parameters used for different validation matrix.

S.N.	Validation Parameter
1	Accuracy
2	Precision
3	Recall
4	f-score
5	ROC(AUC)
6	Specificity
7	Sensitivity

V. CONCLUSION AND FUTURE WORK

For practical implementations, most of the works are done either using Python for preprocessing and augmentation operations on dataset or MATLAB RyyyyX for deep learning model development using primary (some private dataset) or secondary datasets (standard research dataset). In works with standard datasets main robust dataset used is HAM10000 ("Human Against Machine with 10000 training images") dataset [24] ,a large collection of multi-source dermatoscopic images of common pigmented skin lesions standard research dataset published as a standard dataset for machine learning in research community and overtly accessible in the course of the ISIC archive[25].

Further, considering the research gaps and needs of the practical application of the work, can be extended to deliver with simple hand held devices like mobile cameras and also can be focused to the development of the Expert Diagnostic Intelligence Systems for the new data available in any form structured or unstructured for example Big Data. In orientation to the extension of the works an interface with prescription can be delivered.

Table 3: Literature and performance statistics

S.N.	AUTHOR(S)	YEAR	DATASET	TECHNIQUE	No of images	Imaging Modality	ACCURACY
1	Puja [4]	2019	HAM10000	Pretrain CNN with VGG16/VGG19	850	Dermatoscopic	91%
2	Jayashree Hajgude and A Bhavsar[5]	2019		SVM and CNN	408		90.70%
3	N Vikranth Kumar,P Vijeeth K[6]	2019	kaggle	SVM	1700		90%
4	Kyamelia Roy, Sheli Sinha Chaudhuri[7]	2019	Xiangya Derm	Segmentation techniques		CT	
5	ZHE WU,SHUANG ZHAO,YONGHONG, XIAOYU HE,XINYU and YI LI[8]	2019	Xiangya Derm	CNN	2656	Dermatoscopic	92.90%
6	Felix Q. Jin and Michael Postiglione[9]	2019		Neural Network	246 test	USG	
7	Jainesh Rathod and Vishal Waghmode[10]	2018		CNN			70%
8	Anabik Pal,Sounak Ray and Utpal Garain[11]	2018	ISIC 2018	Pre-trained CNN	10015		77.50%
9	Li-sheng Wei,Quan Gan and Tao Ji[12]	2018		SVM		CT	85%
10	Shashi Rekha G1,Prof.H.SrinivasaMurthy[13]	2018		SVM			80%
11	R. S.Gound and PriyankaS.Gadre[14]	2018	Edinburgh Research and Innovation	SVM	100		92%
12	S.Kalaiarasi,HarshKumar[15]	2018		ANN			
13	Archana Ajith,Vrinda Goel[16]	2018		SVD with DWT and DCT			80%
14	Nisreen I. Abo Dabowsa and Nasser M. Amaitik[17]	2017	Benghazi Hospital, Libya	CBR,ANN			80%
15	Nisha Yadav and V Kumar [18]	2016	HSV/Lab	ANN		Dermatoscopic	
16	Pravin S. Ambad and A. S [19]	2016		DWT and ANN			90%
17	Vinayshekhar B Kumar[20]	2016	Private	Machine Learning			95%
18	Rahat Yasir and Md. A. Rahman[21]	2014		ANN		ELM	90%
19	Damilola A.Okuboyejo[22]	2013	DSSA	Segmentation and ANN		Dermatoscopic	
20	Hadzli Hashim, Rozita Jailani [23]	2002	HUKM	Segmentation and Histograms		Cell Phone	

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