Proceedings of the International Conference on Intelligent Sustainable Systems (ICISS 2017)
IEEE Xplore Compliant - Part Number:CFP17M19-ART, ISBN:978-1-5386-1959-9

Automated Detection of Dermatological Disorders through Image-Processing and Machine Learning

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Abstract- **Dermatological Diseases are one of the biggest medical issues in 21st century due to it's highly complex and expensive diagnosis with difficulties and subjectivity of human interpretation. In cases of fatal diseases like Melanoma diagnosis in early stages play a vital role in determining the probability of getting cured. We believe that the application of automated methods will help in early diagnosis especially with the set of images with variety of diagnosis. Hence, in this article we present a completely automated system of dermatological disease recognition through lesion images, a machine intervention in contrast to conventional medical personnel based detection. Our model is designed into three phases compromising of data collection and augmentation, designing model and finally prediction. We have used multiple AI algorithms like Convolutional Neural Network and Support Vector Machine and amalgamated it with image processing tools to form a better structure, leading to higher accuracy of 95.3%.**

Keywords: Dermatological Disorders; Machine Learning; Image Processing; Automated Disease Diagnosis; AI algorithm; Computer Vision Techniques.

I INTRODUCTION

[2] Dermatological Diseases, due to their high complexity, variety and scarce expertise is one of the most difficult terrains for quick, easy and accurate diagnosis especially in developing and under-developed countries with low healthcare budget. Also, it's a common knowledge that the early detection in cases on many diseases reduces the chances of serious outcomes. The recent environmental factors have just acted as catalyst for these skin diseases. Our focus-eczema, herpes, melanoma, psoriasis- when detected at an early stage can put someone's life out of danger.

The general stages of these diseases are as: STAGE 1- diseases in situ, survival 99.9%, STAGE 2- diseases in high risk level, urvival 45-79%, STAGE 3-regional metastasis, survival 24-30%, STAGE 4- distant metastasis-survival 7-19%.

As is evident from this data if a system can determine the disease in very least second stage or better in first stage itself, the survival rate is so high that a life can be protected. This has been our motivation throughout as we developed a machine learning based predictive model to determine these diseases in the first stage itself. This determination poses few too many problems like the generation of the dataset for the deep learning model to train on, creating the perfect architecture to achieve the maximum accuracy for efficient determination. The first problem was solved by implementing data augmentation while the second was solved creating a completely new model by amalgamating Convolutional Neural Network and Support Vector Machine.

The reports published by reputed institutions like American Joint Committee on Cancer clearly mention the need to for identification of skin diseases in the primordial stages itself. .
Our paper very comprehensively explains each and every process by segregating the same in five more sections. The second section discusses the previous works been done in the same field, third section gives a overview of our work, fourth section discusses each component in depth, fifth section provides our result and final sixth section elucidates on our references. Finally the impetus for our work has been the fact that this could eventually be put to some bigger cause.

II RELATED WORKS

The authors [1] have tried to address the same problem using image analysis techniques. The work uses the technique of noise removal and subsequent feature extraction. After the noise removal, the image is fed into classifier for further feature extraction process and finally the prediction of the disease.
Most of the earlier publications focused on feature extraction and then subsequent disease prediction was done. Papers [6,3] have used Artificial Neural Network for dealing with this complex problem while papers [2,4,5] have used machine learning algorithms for the task. Computer vision techniques have played a major role in many previous literatures. As is evident, the publishers have utilized the image processing techniques to accomplish the pre processing task. In the similar way we also try to implement the computer vision techniques, but out implementation mainly focuses for dataset augmentation. However, the authors [8] have very acutely used

the skin color as the main classification pattern for determining the malignant and benign lesions. The skin color in each disease appears very differently and in each disease it follows a same pattern. By identifying this pattern, the classification task can be made much simpler and effective which has been the case for M. Shamsul Arifin et.al.

Throughout the world researchers are working to solve this ubiquitous problem. Kabari et al [8] used artificial neural networks for the determination of skin diseases with an accuracy of about 90%. Through this paper we also try to answer this problem but the main difference between our work and the previous works being our use of machine learning and deep learning together to generate a model giving an accuracy of about 95.3%

III METHODOLOGY

Our model is designed in three phases which areas follows:

A. *Phase 1*

First phase of the model involves dataset collection and data augmentation. The dataset was completely created by us gathering the images of different diseases from different sites[15] etc. The original dataset consisted of around 3000 images which after augmentation becomes close to 10,000.

B. *Phase 2*

This is the most important phase of our model. It involve designing our model as well as training it. The model was trained using Jetson TX-2 Development board on the dataset we created. The model after training, was saved in the pkl format with the corresponding weights associated.

C. *Phase 3*

This is the result phase of our model. The image to be identified is used as an input. After converting it into array, it is fed into our trained model which after being broken down to corresponding features, is predicted by the model.

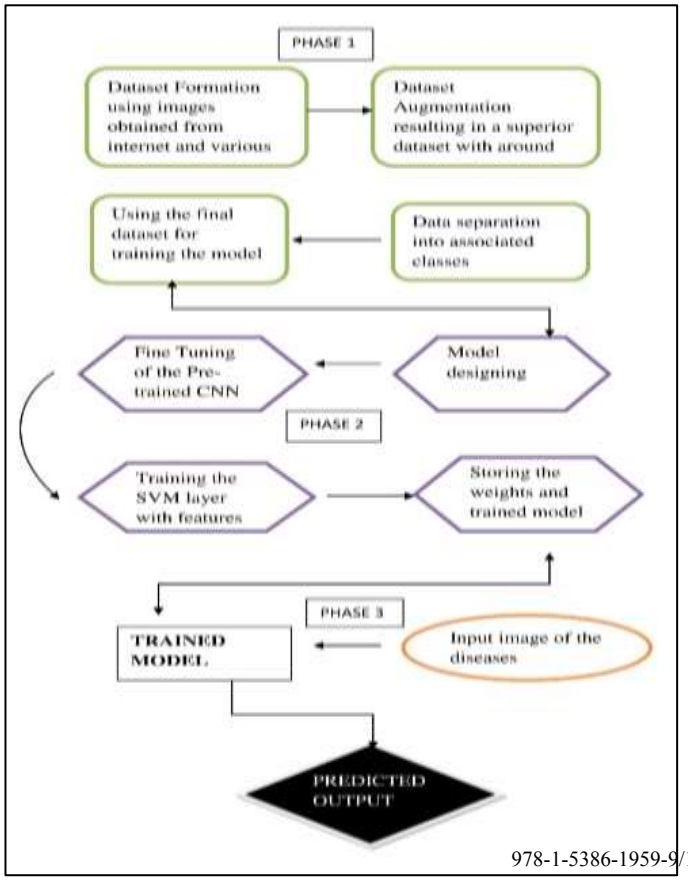

Figure 1 Work Flow

IV. COMPONENTS OF METHODOLOGY:

A. *PRE-PROCESSING*:

Pre-processing of images and features is very important task for it helps in reduction of time for training, by removing unnecessary images, and helps in improving the efficiency of the model, by increasing the dataset. The pre-processing includes:

- Creating the dataset
- Data augmentation
- Data separation

Dataset: creating the dataset is a very challenging task. We used around 3000 images in our initial dataset sub-divided into four classes- Eczema, Herpes, Melanoma, and Psoriasis. Each image in the dataset gives in a different feature for our model to train on like the color of the disease, its shape or the body part it affects.

Features are basically the significant estimable property or characteristic of an event under observation. If the images are repetitive within a dataset, the model gets trained which leads to the over fitting of data and makes the model more specific than providing the general view and better results. The dataset thus needs to be winnowed in order to remove any repetition of the images and hence the over training of model on a single feature. The dataset so made, tends make the training part even more complicating.

Data augmentation: the repetition of images is not the factor affecting the accuracy of a model. Being trained on a very less dataset [rt is another issue that we deal in this paper.

Imbalanced dataset is the one which suffers from the problem of classes not being in proportion. This causes a machine learning model to generate fake accuracy reports with the imbalanced dataset. With our model we have tried to evade this problem by following techniques.

For our dataset, we managed to generate more than 10,000 images from our initial 3000 ones with each corresponding class having around 2,500 images. This was made possible by the numerous augmentation techniques used by us like:

1. SMOTE (Synthetic Minority Over-Sampling Technique) - it is an oversampling method which can create synthetic samples from minor classes instead of just copying them. The algorithm selects two or more similar instances (using a distance measure) and perturbing an instance one attribute at a time by a random amount within the difference to the neighboring instances.

2. Changing the perspective of images- this is a very simple

technique to augment the dataset. Simply by rotating the images, we can extract more features from it.

3. Implementing computer vision techniques: we used computer vision for further increasing our dataset. We implemented gray scaling, blurring, increasing the contrast, changing the color channel, sharpening, reducing the noise and smoothing on our existing one thereby generating new images.

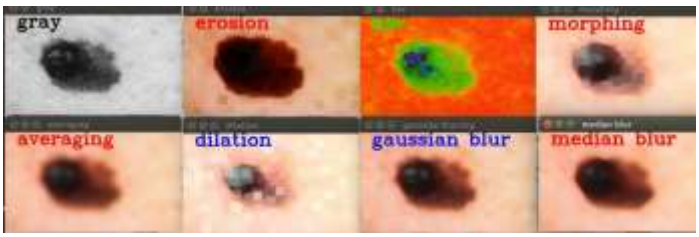

Figure 2: Showing Different Image Processing used in the system.

Data Separation: After the creation of the dataset, we separated each image into sub-classes thereby making it easier for our model to learn efficiently the features of each image and thereby generating a high accuracy.

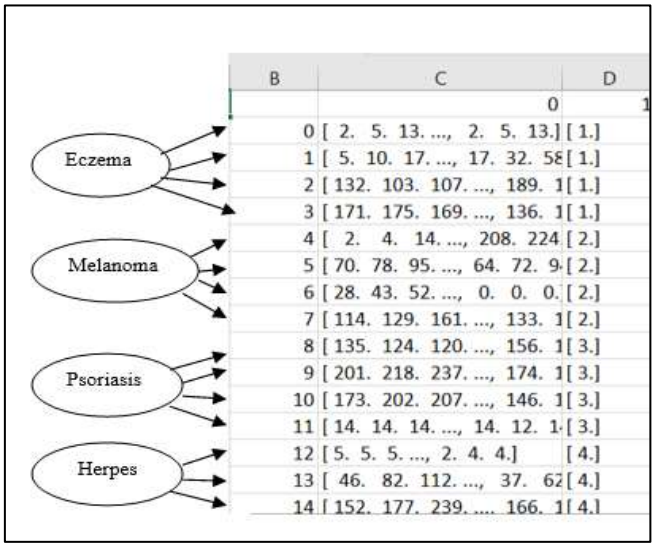

Figure 3: Screenshot of array of Separated images obtained after training the network

B. *DESIGNING THE MODEL:*

Our model is an amalgamation of Convolutional Neural Network (CNN) and Support Vector Machines (SVM). This was done to increase the accuracy of the entire structure.The data obtained after pre-processing is processed using CNN. The features extracted by CNN are then passed through the SVM for further classification of the diseases.

CNN ARCHITECTURE: Convolutional Neural Networks can take up a lot of time for getting trained. Even on small dataset with a good GPU like Jetson TX-2, the training can take upto few days. However utilizing fine tuning on a CNN architecture can save a lot of time during training process.

- **Fine Tuning**: Training a Convolutional network on a small dataset could largely affect its ability and often leads to overfitting. But when a model is trained on a larger one, this problem is removed. Fine tuning is basically a procedure in which we train a pre-trained model on our small dataset by replacing the final layer of the Convolutional network with our layer having the same number of output classes as in our dataset or by lowering the learning rate of the model. The choice depends upon the situation and in our case we truncated the final layer (softmax layer) according to our requirements.

- **VGG-19 Model**: We used VGG-19 architecture as our base model. The final layer of VGG-19 architecture is labeled as FC-1000 signifying for fully connected layer with 1000 as the size of the output image. This layer is activated using SOFTMAX activation for generating the output and finally replaced by SVM layer for classification. The model was trained on the IMAGENET dataset containing 1.2 million labeled categories. For the fine tuning process, we removed the softmax layer with 1000 classes as output and replaced it with layer having 4 as output.

ReLU activation function: Each layer in the Convolutional network is activated using ReLU function. ReLU stands for Rectified Linear Unit.
The function is defined as: $f(x) = \max(0, x)$;where x is the input to the neuron
The function is very important when it comes to neural network implementations because of its efficient grading propagation which inhibits any gradient vanishing or exploding issues. It also helps in efficient computation as it only allows comparisons, additions or multiplications.

- *SOFTMAX activation*: The final layer (FC-1000) of the VGG-19 network is activated using SOFTMAX function for prediction tasks. The function is given by:

$$\sigma(z)j = \frac{e^{zj}}{\sum_{k=1}^{K} e^{zk}}$$

For j=1,2,.....

The softmax function is a generalization of logistic function that squashes a$\sigma(z)$ K dimensional vector z of arbitrary real values to a K-dimensional vector of real values in the range [0,1] that add up to 1 thereby giving a prediction about classification.

- *Hinge Loss*: In the softmax activation layer we utilize the 'hinge' loss. The choice facilitates the usage of SVM classifier at the end of the fully connected layer. The hinge loss is basically a loss function used for training classifiers. For an intended output t = ±1 and a classifier score or accuracy 'y', the hinge loss function is given by:

$$l(y) = \max(0,1 - t.y)$$

SVM CLASSIFIER: After the model is trained by changing the final layer output dimension to 4 and loss function to 'hinge',the SVM classifier is used. The SVMs are the supervised machine learning algorithm. Given a set of training examples, each marked as belonging to one or the other categories, an SVM training model builds a model that assigns new examples to one category or the other making it a non-probabilistic binary classifier.

In our model we use the SVM for the prediction task after it has been trained on the features extracted by the final Convolutional layer.

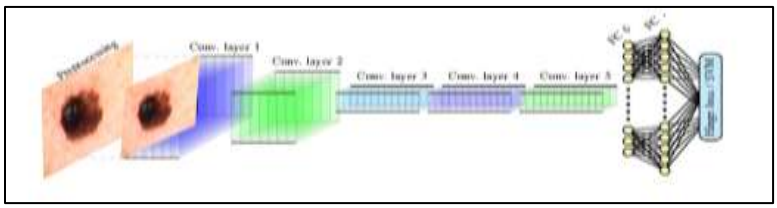

Figure 3-Complete architecture of the model after replacing FC-1000 layer with SVM Classifier

C.*MODEL TRAINING*

The training process of our model is divided in to two parts. First we train the pre-trained model on our reduced dataset and then we take the trained features from the final Convolutional layer and train the SVM classifier. The final layer of the CNN model i.e. FC-1000 is replaced by our SVM layer which gets trained on the features extracted by the complete model. The final trained weights or the features and the trained model is saved for further utilization.

The features from the final Convolutional layer are directly used as an input for the SVM classifier. Thus the dataset for the SVM layer isn't the input image but the trained features which are then converted to vectors by the SVM and stored. The CNN layers tend to extract features from the images very efficiently. Thus the SVM training results in precise results.

D. PREDICTION

The prediction is done by the trained SVM model. The stored model is used for the prediction purposes and the image is passed through each Convolutional layer after which the extracted features are provided to the SVM layer which after converting it to vectors compare with the existing weights.

V .RESULTS

After data augmentation, making a dataset of about 10,000 images we have used many images for testing as well. The images were converted into arrays and then they were broken down into features by CNN and then trained by SVM as mentioned above. Accuracy obtained after training with CNN alone was about 91% which was increased to about 95.3% when amalgamated with SVM. Following is the image of the test performed by us on some arbitrary images from the internet producing accurate results.

VI. CONCLUSION

This system provides a comprehensive tool which can be used in order to predict the dermatological disease of the potential patients for the aforementioned diseases covered in the paper. After including several diseases with higher occurrence than a threshold, the System would be further incorporated into the android and IOS mobile systems and on the internet to increase the use of such system by the people living in remote areas with lesser medical advancements and techniques. People would be able to input the image into the app or online portal and would get the prediction without any expenses or availability issue.

Figure 4 (A, B, C): Examples of Prediction on Arbitrary online images.

VII.ACKNOWLEDGEMENT

This work was supported by the Department of Biotechnology, Government of India [No. BT/PR5402/BID/7/508/2012].

VIII.REFERENCES

[1] Pravin S. Ambad, A.S. Shirsat "A Image analysis System to detect Skin Disease", IOSR Journal of VLSI and Signal Processing-2016

[2] VinayshekharBannihatti Kumar, Sujay S Kumar, Varun Saboo "Dermatological Disease Detection Using Image Processing and Machine Learning, IEEE-2016

[3] RahatYasir, Md. Ashiqur Rahman, Nova Ahmed "Dermatological Disease Detection using Image Processing and Artificial Neural Network", 8th International Conference on Electrical and Computer Engineering-2014

[4] Sunnel Kumar, Ajit Singh "Image Processing for recognition of skin diseases, International Journal of Computer Applications-2016

[5] DamilolaA.Okuboyejo, Oludayo O. Olugbara, Solomon A. Odunaike "Automating, Skin Disease Diagnosis using Image Classification", Proceedings of the World Congress on Engineering and Computer Science-2013

[6] L.G.Kabari, F.S. Bakpo "diagnosing Skin Diseases using Artificial Neural Network", IEEE-2009

[7] Segmentation of skin cancer images- ScienceDirect article-1999

[8] M. Shamsul Arifin, M GolamKibria, Adnan Firoze, M. Ashraful Amin, Hong Yan "Dermatological Disease Diagnosis using Color-Skin Images", Proceedings of the 2012 International Conference on Machine Learning and Cybernatics-2012

[9] Fine tuning techniques- https://machinelearningmastery.com

[10] Machine learning course by Andrew Ng https://coursera.org

[11] A-Z introduction to deep learning by Kiriel Ermacko https://udemy.com

[12] Yichuan Tang "Deep Learning using Linear Support Vctor Machines",International Conference on Machine Learning-2013

[13] Jospeh Lin Chu "Using Support Vector Machines, Convolutional Neural Network and Deep Belief Networks for Partially occluded Onject Recognition-Thesis report at Concordia university-2014

[14] Jos van de Wolfshaar, Mahir F. Karaaba, Marco A. wiering "Deep Convolutional Neural Networks and Support Vector Machines for Gender Recognition", Computational Intelligence, IEEE Symposium-2015

[15] Images from © Diepgen TL, Yihune G et al. Dermatology Online Atlas (www.dermis.net) http://homepages.inf.ed.ac.uk/rbf/DERMOFIT/

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