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CNN and Transfer Learning methods for enhanced dermatological disease detection

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***Abstract*—Since skin diseases generally badly affect lives, the earlier and more accurate the diagnosis, the better the chances of effective treatment and a better prognosis. Deep learning applications, especially CNNs, has revolutionized the domain of disease classification, significantly increasing the accuracy of diagnoses for such common conditions and facilitating early interventions. The huge success behind the ongoing project motivated advancements of the developing in CNN techniques towards detection of skin disease by using the concept of Transfer Learning. So, the older models, which had employed it for detecting Eczema and Psoriasis based on the architectures involving deep CNNs. The Inception ResNet v2 architecture improved the accuracy of that model, with some practical implementations via smartphone integration and web server integration. Some of those innovations are as follows in our project. The earlier work used different CNN architectures. Our approach involved Transfer Learning with a pre-trained ResNet50 model to try to improve performance and efficiency using features learned from large-scale datasets. This reduce the complexity and enhance the accuracy. Besides Transfer Learning adaptation, our project encompasses elaborate preprocessing techniques like resizing, normalization, and data augmentation in fine-tuning the dataset for further model fine-tuning. It has 97.6% accuracy, 95% precision, 99.4% recall, and 97.4% F1-score. rad-CAM techniques have been employed to visualize and interpret model predictions. This final model has been a pragmatic and accessible tool for early detection and diagnosis of skin disease. The feature here is an attempt to provide a more accurate, efficient, and user-friendly diagnostic solution through the incorporation of advanced methods of Transfer Learnin3g and visualization.**

***Keywords*—eczema; psoriasis; dermatology; CNN; transfer learning**

I. [1]INTRODUCTION

CONSIDER an example of a skin disorder which not only has an impact on the physical health of an individual but also their mental health. Millions of people all over the world suffer from diseases such as eczema and psoriasis, which severely impact the quality of life. The catch here is, such diseases are hard to diagnose in the early stage and exactly because of the heterogeneity and complexity of the symptoms involved. This shall be overcome using the Convolutional Neural Network (CNN) part of Deep learning and AI that would facilitate fast and accurate detection of automated skin diseases. Our aim will be to expand the CNN-based models by exploiting Transfer Learning. It is relatively feasible to deploy pre-trained models like ResNet50 at the cost of enhancements in computational resources and accuracy. Looking forward to being able to develop an easy-to-use and pragmatic early-stage disease detection tool for skin diseases that bridges the hype of AI with reality on the ground in healthcare.

In order to enhance our model, these would entail resizing and standardizing our data as well as sophisticated data augmentation techniques. The confidence in AI-based healthcare solutions will be increased by measuring performance metrics such as precision, recall, accuracy, and F1-score for the aforementioned models to explain model predictions like Grad-CAM.

Ultimately, our initiative aims to develop a quick and effective way to identify skin conditions, which will alleviate the strain on healthcare systems and improve patient outcomes. It is a field of AI-based healthcare solutions that will revolutionize patient care and diagnostics by using sophisticated visualization techniques and Transfer Learning.
Skin diseases make up part of the currently sweeping and on-the-rise global health issues, plaguing millions. The scale is enormous with millions unable to live normal lives as a result of their debilitating condition. However, the great minds among the scientists and researchers keep striving day and night for some innovative diagnostic method and treatment for these diseases. Deep Learning and Machine Learning breakthroughs:

The last years have seen spectacular growth in the fields of machine learning and deep learning, giving tremendous promise in this fight against skin diseases. These advanced technologies have finally enabled researchers to construct the best models and methods for detecting and diagnosing problems with skin. Two of them are:

1. Detection of Psoriasis: This will detect the presence of psoriasis in patients, depending on the characteristics of their skin color and texture. The system has achieved shocking success rates in accuracy, thus bringing new hope to patients suffering from this disabling disease.
2. Eczema Detection: This model detects the size of the affected sites and severity of eczema. It uses the color and texture features of an image, which makes it display the potential power that may be offered in dermatological analysis by machine

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learning.

This research builds on earlier studies. Lowe et al. (2014) [2] discussed the immunological backgrounds of skin diseases, which provide a knowledge basis for molecular and cellular structures concerned in image-based classification. Feature extraction, as Al Abbadi et al. (2010) [3] emphasized, plays an important role in disease detection with accuracy. It aims to improve methods for feature extraction that are either based on the texture, colour histograms, and feature maps through deep learning that can help boost model performance maximally. Alam et al. (2016) [4] proposed an eczema severity measurement: the potential that AI methods are able to facilitate automatic assessment. The work of this study aims to generalize this approach in the determination of the severity level of a set of dermatological conditions like eczema, psoriasis, and acne through image processing and machine learning.

Detection of skin diseases involves some of the biggest challenges such as the performance maximization of algorithms in handling large heterogeneous data. As set out by Khan et al. (2020) [5], comparative study of machine learning classifiers in medical data is key to the building of robust models for generalizability across different populations and large databases of images. This study overcomes this limitation by capitalizing on the strength of CNNs, employing the pre-trained ResNet50 model. In this work [7], a study was conducted into eczema detection and recognition in cloud computing environment with focus on scalability of medical application. This study,[8] also utilize transfer learning technique in diagnosing skin diseases from images exhibiting the relevance of pre-trained models to dermatological purposes. The authors [9] use machine learning algorithms for skin disease detection, to illuminate improvements in algorithmic images in classification. This research [10] provide the use of CNN skin disease detection with the help of deep learning in the medical imaging domain. This survey forms the basis to get an appreciation of the existing paradigms in skin disease diagnosis and classification techniques using machine learning along with image processing and computational techniques.

Additionally, diagnostic software availability is also necessary. Shawkat Abdulbaki et al. (2019) [6] emphasized the cloud computing-based detection of eczema using web-based applications. The present work is aimed at designing web-based applications for the classification of skin diseases so that resource-constrained classification becomes achievable for clinicians and researchers. A very promising approach towards exploitation of pre-trained CNN models in medical image segmentation, classification, and even decision support, which is provided by Janoria et al. (2020). It employs fine-tuning of the pre-trained ResNet50 model for our skin disease.

II. Methodology

The diagnosis of the skin disease process as well as various CNN models is elaborated under proper subheadings. Figure 1 depicts the details of working procedure. The working procedure starts from data collection and followed by classification of the collected images. Removal of noisy images and image resizing performed. Image augmentation are performed by scaling image for dataset expansion then performed 2 folding. Then the features are extracted using pretrained CNN model Resnet50 and ultimately classification is done and achieved better accuracy.

A. Dataset Collection

Our skin is our biggest and most apparent organ - it is an insulating barrier to all those environmental influences around us and at the same time is an integrated component of our health and hygiene as a whole. On the other hand, it is appalling that more than 900 million people in this world suffer from some form of skin disease from a small, non-significant irritation to death-dealing forms.

1) Effects of Skin Diseases in Everyday Life

Diseases that affect the skin significantly restrain most people from going about daily life, causing them discomfort and cause emotional distress as well as social humiliation. Some of the most common diseases that infect skin are eczema and psoriasis.

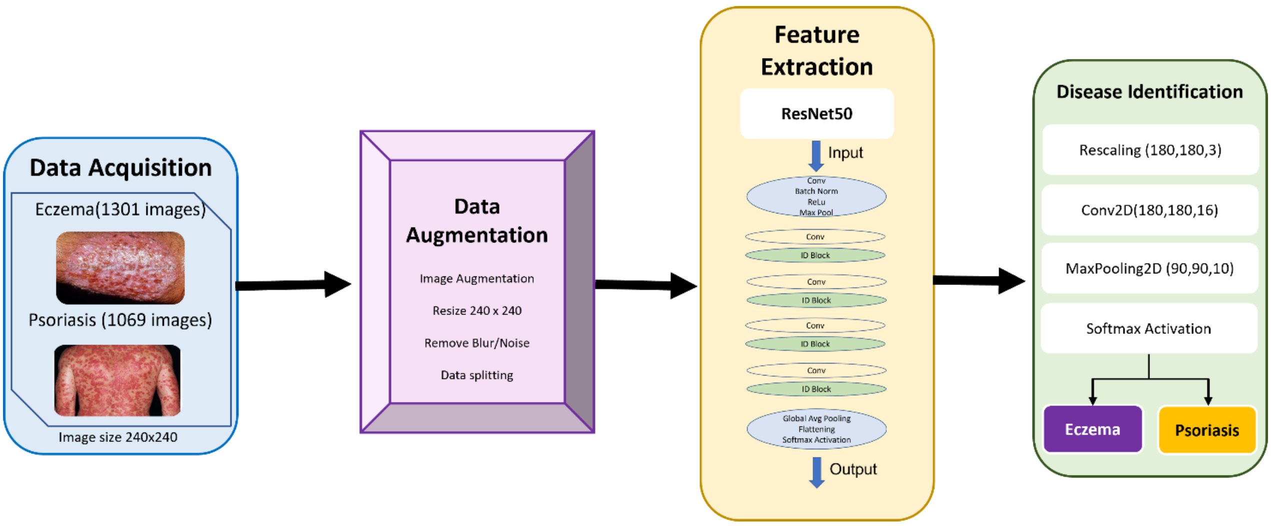


Fig. 1. Block diagram of Deep Learning-Based Skin Disease Prediction Model (Proposed)

Eczema is atopic dermatitis, or inflammation of the skin caused by dry, scaly, and itchy skin. Psoriasis, on the other hand, is an immune system-mediated disease where there is creation of red scaly patchy areas of the skin.

2) Collection and Preparation of Dataset

Downloaded a complete dataset of images from trusted sources like DermNet NZ, Dermnet Skin Disease Atlas, and Kaggle to better understand and diagnose the diseases. Noise and low contrast images are filtered out by hand and got a cleaned-up dataset of 2368 images.

With our dataset of 1301 eczema and 1067 pictures of different regions of psoriasis for each category of illness being well-presented. Examples can be viewed on Fig. 2, given below as being part and parcel of the database used.

To be better diagnosed, images played a paramount integral part as additions to both training and the testing set on machines to let us come out and propose far much more appropriate diagnostics for this range of dermatosis.

Improved the lives of millions of individuals worldwide through the efficient utilization of these technologies and data by improving on diagnosis and the subsequent treatment for eczema and psoriasis.

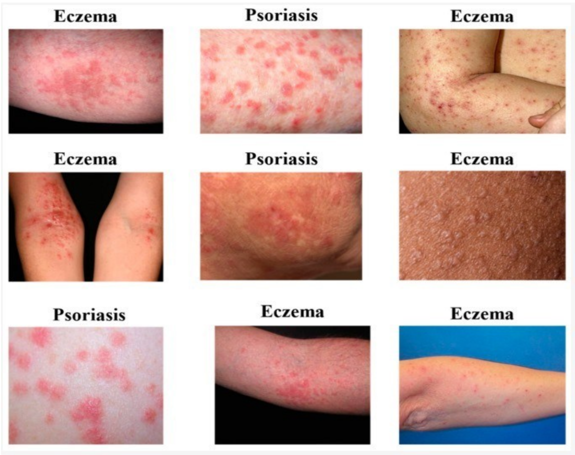


Fig. 2. Image samples of skin disease dataset of Eczema and psoriasis

Our dataset is a treasure of images that can all relate to different diseases as regards skin issues. These would be the training set of our model for the first time. Being so massive, the size of the database makes it a relatively straightforward thing for us to classify images under a class of diseases the skin might be exposed to.

Before getting the model to actually train, pre-processing and cleaning the dataset had done.

This careful process implies that our dataset should be the best possible and from it is where our model learns its data. For that reason, set the stage for the model so it might thrive well during the diagnosis of diseases in relation to skin issues.

This feature-based model relies completely on features which have been derived from images by architectures of the CNN. Those features are the precursors with which our model distinguishes other skin conditions affecting a patient. Empowered the model to identify trends and characteristics, which may well be hidden within those images to not be noted by experts and applying CNNs. With our features extracted the model proceeds for classification using a dense layer architecture of our CNN. This critical step enables the model. It provides highly accurate diagnosis and will assist in early and effective treatment.

With the power of deep learning, an outstanding functionality to our model stands. It picks up even the minutest abnormality present in the image of the skin which may go unobserved by the keen eye of an expert that makes the early and accurate diagnosis.

Creating an effective system for diagnosing and managing Eczema and Psoriasis that improves the lives of millions will be the purpose.

TABLE I
IMAGES OF ECZEMA AND PSORIASIS

Disease type	Eczema	Psoriasis
Training data	1040	856
Validation data	261	211
Total	1301	1067

B. Variance in the Data

Variation in the data is a very strong method that helps to artificially augment our dataset. Let us create a whole new image different from all that has already come from earlier ones such images may tend to commit less overfitting and the ability for generalization.

The data augmentation procedures are described here:

The brightness of our images enhanced by 20% to simulate different lighting conditions. enhancing the contrast of our images by 10% to accentuate details.

Random Rotation: Randomly rotate our images by 5 degrees to simulate different orientations.

Horizontal Flip: Flip the images horizontally to simulate mirror reflections.

Combining them to generate five variations for each sample image into a more comprehensive and diverse set.

C. Dataset Analysis

After that we add the new data to our dataset had totally 2368 images for the dataset. Dataset is divided into training and testing sets with 80:20 split. Training set had 80% of the total images (1894 images), and our testing set consisted of 20% (474 images). In this way, the model would have been trained on a variety of images and tested on another independent, unbiased set.

In order to avoid biased outcome, make sure that our testing images never mixed with training and validation sets. It meant our test set would comprise a whole different set of images, thus giving a proper and performative measure of its abilities.

D. Deep CNN Architectures

In fact, CNNs are supervised machine learning algorithms, and they're very good for image recognition and classification. In the case of skin disease diagnosis, CNNs perform very well. Five different architectures of CNN are tested, all distinctive in their unique strengths and characteristics.

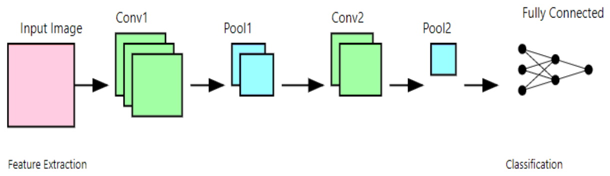


Fig. 3. Convolutional Neural Network (CNN) architecture

ResNet-50 is the strongest image classification model utilized in skin disease detection applications. Utilizing ResNet-50 in an effort to obtain precise skin disease classification. It has assisted us in creating a trustworthy diagnostic tool.

It means the utilization of ResNet-50 for the best available power in complex patterns and features extracted by images in making our model more robust for disease detection.

ResNet-50 is a deep neural network that contains residual connections, which has been famous for its excellent ability to learn complex patterns with ease and efficiency during training. Hence, we utilized the pre-trained model called ResNet-50 that was trained on a vast collection of images. In this way, the model tapped into the knowledge acquired by its initial training phase, thus improving performance and faster convergence.

The pre-trained ResNet-50 architecture, unfroze only the final dense layer with frozen weights of the rest of the layers. This cautious design approach facilitated fine-tuning of this model for finding those characteristics peculiar to our skin disease dataset and yet not losing features inducted by the strength of the pre-trained weights.

Initialize the dense layer randomly, fed it our skin disease dataset, and then fine-tuned the related weights using optimization techniques through back-propagation. In this manner, the strengths of ResNet-50 was leveraged and accomplished transfer learning for skin disease classification.

With the help of ResNet-50 and after fine-tuning for our very task, it made a fairly strong model good at classifying the diseases as such. As it stands out here, an approach using a powerful ResNet-50 helps demonstrate the strengths of transfer learning in handling big complex medical classifications using deep networks.

E. Optimization Algorithms

Optimizers are most essential to deep learning since they work behind the scenes of weights and learning rates for fine-tuning those behind Convolutional Neural Networks, or CNNs.

*1) Adam **Optimizer:** Adaptive Moment Estimation*

Adam is an optimizer that utilizes the learning process as the foundation for a modification in the learning rate. It adjusts each parameter as an individual in equations (i) to (iv). It maintains the exponentially decaying past gradients and maintains the average of past squared gradients too. The equations as presented in (i) to (iv) with which the Adam optimizer operates to update the weights.

Vt = β1 * Vt-1-(1- β1) * 9t

S_t = β2 * St-1-(1- β2) * g_t

$$\Delta\omega_t = -\eta \frac{Vt}{\sqrt{(St + \epsilon)}} * gt$$

$\omega_t+1 = \omega_t + \Delta\omega_t$

η: Learning rate initially

gt: Gradient at t along ω^j

Vt: Exponential Average of gradients along ω_j

S_t: Exponential Average of squares of gradients along ω_j

β1, β2: Hyperparameters

The Adam optimizer updates the node weight considering historical average gradients. The default for β1, β2 are 0.9 & 0.999 respectively.

SoftMax Activation

SoftMax function is applied to different machine learning algorithms, most notably in a neural network classification. The softmax function derived in the equations (i) and (ii) to is applied for the transformation of raw scores, or neural network logits into probabilities. It maintains the values of the outputs within the interval (0, 1) and sums to 1, thus it can be treated as probabilities these output values. It is used to solve the multi-class classification problem.

Derivative of SoftMax

Let's compute D_jS_i for arbitrary i and j:

$$D_jS_i = \frac{\partial s_i}{\partial a_j} = \frac{\partial \frac{e^{a_i}}{\sum_{k=1}^{N} e^{a_k}}}{\partial a_j} \qquad \text{(i)}$$

Using the quotient rule of derivatives. For: $f' = \frac{g(x)}{h(x)}$

$$f'(x) = \frac{g'(x)h(x) - h'(x)g(x)}{[h(x)]^2} \qquad \text{(ii)}$$

In our case :

$g_i = e^{ai}$

$$h_i = \sum_{k=1}^{N} e^{ak}$$

Note that no matter which a_i we compute the derivative of h_i present in the equation (ii) for, the answer will always be e^{aj}. This is not the case for g_i, however. The derivative of gi w.r.t. a_j is e^{aj} only if $i=j$, because only then g_i has a_j anywhere in it. Otherwise, the derivative is 0.

Going back to DjSi; started with the $i=j$ case. Then, using the quotient rule have equation (iii)

$$\frac{\partial \frac{e^{a_i}}{\sum_{k=1}^{N} e^{a_k}}}{\partial a_j} = \frac{e^{a_i}\Sigma - e^{a_j}e^{a_i}}{\Sigma^2} \qquad \text{(iii)}$$

$$\frac{\partial \frac{e^{a_i}}{\sum_{k=1}^{N} e^{a_k}}}{\partial a_j} = \frac{e^{a_i}\Sigma - e^{a_j}e^{a_i}}{\Sigma^2}$$

$$= \frac{e^{a_i}}{\Sigma}\frac{\Sigma - e^{aj}}{\Sigma}$$

$$= Si(1 - Sj) \qquad \text{(iv)}$$

For simplicity $\sum$ stands for $\sum_{k=1}^{N} e^{ak}$. Reordering a bit.

The final formula expresses the derivative in terms of itself as in equation (v).

Similarly, another case:

$$\frac{\partial \frac{e^{a_i}}{\sum_{k=1}^{N} e^{a_k}}}{\partial a_j} = \frac{0 - e^{a_j} e^{a_i}}{\Sigma^2}$$

$$= \frac{-e^{a_j}}{\Sigma} \frac{e^{a_i}}{\Sigma} = SjSi$$

$$DjS_i = \begin{cases} s_i(1 - s_j) & i = j \\ -s_j s_i & i \neq j \end{cases} \quad \text{(v)}$$

$$DjS_i = i(\delta_{ij} - s_j)\delta_{ij} = \begin{cases} 1 & i = j \\ 0 & i \neq J \end{cases} \quad \text{(vi)}$$

To summarize:

observing this clear case-by-case dissection, but mathematicians are the ones who take greater delight in being succinct and astute than programmers. For this reason, several "condensed" versions of the same equation can be found in different parts of the literature. Using the Kronecker delta equation (vi) function is among the most popular ones to write.
Which is the same thing, of course. A few further formulations can be found in the literature is substituting I, the identity matrix, whose members express δ in the matrix form, for δ by matrix form of Jacobian. Instead of using Kronecker delta, use "1" as the function name in this way, *D*-*j*., *S*-1. =, *S*-*i*.,1, *i*=*j*. −,*s*-*j*... In this case, 1(i=j) denotes a value of 1 when i=j and 0 otherwise. When calculating more complicated derivatives that rely on the SoftMax derivative, the condensed notation is helpful because otherwise, It would have to spread the condition everywhere.

III. Performance Analysis

A computer system with an Intel Core i5 processor, 16 GB of RAM, and Nvidia Rtx-3050 graphics was used for the execution. The models have been collaboratively trained using the Keras framework with a TensorFlow. The information has been split 80–20 for training and validation respectively. 813 images have been added for model testing.20-epochs 2-fold cross validation has been considered at training and validation. For updating the weights Adam optimizer algorithm has been used. The hyper parameters used are as follows:

InputImageSize:240*240, Epoch :20, Learning rate is 0.0001 with SoftMax classifier and adam optimizer has been used.

A. *CNN Performance Analysis of Training Accuracy, Validation Accuracy, Test Accuracy, and Confusion Matrices*

In the Table II, comparisons of **Inception ResNet V2**, **ResNet50**, for skin disease classification across tasks involving two are present. For **two-class classification**, all models achieved near-perfect training accuracy (~99%). **Inception ResNet V2** and **ResNet50** demonstrated the highest validation accuracy (**97.1%**), outperforming **ResNet50** (**97.3%**).
Inception ResNet V2 (93.0%).Overall, **Inception-based models** performed best in simpler tasks, while **ResNet50** generalized better for three-class classification.

Table II
Accuracy of Various CNN Architectures Using Adam

Architecture	Training accuracy (%)	Validation accuracy (%)	Test accuracy(%)
Inception Resnet V2 with two classifications	99.7	97.1	95.8
Resnet50 with two classification	99.5	97.3	99.49

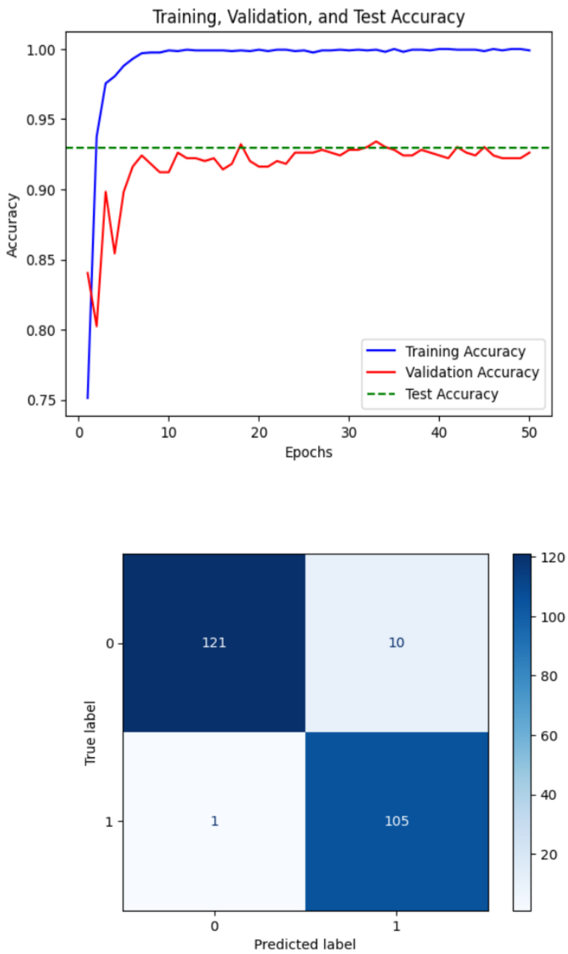


Fig. 4. Accuracy graph and confusion matrix of InceptionresnetV2 with two classifications

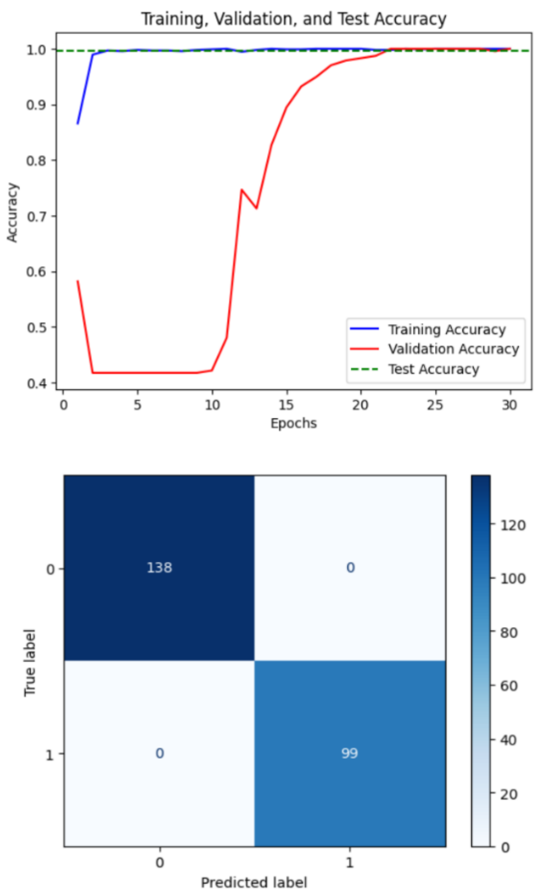


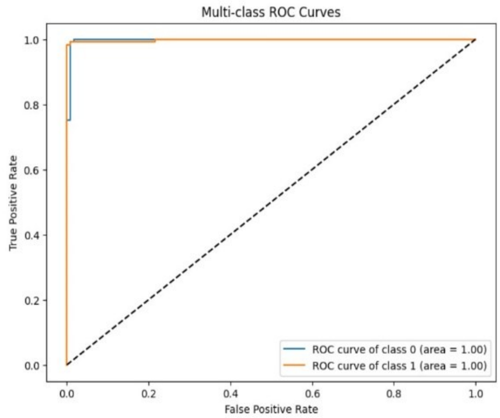
Fig. 5. Accuracy plot and confusion matrix of Resnet50 with two classes

Figure 4 shows the learning curve of the first model and its confusion matrix. Figure 4 The training accuracy has been steadily increasing in Figure 4, to nearly 100% after just a few epochs show that, the model could fit training data very well. Validation accuracy is very close to being constant at levels near training accuracy, thus suggesting minimal overfitting. The test accuracy curve, however has some oscillations, indicating that even though the model was accurate on new data, its generalization performance sometimes varied. In Figure 4, the confusion matrix reveals an overwhelming amount of correct predictions due to high values on the diagonal. A few low values off the diagonal indicate small classification errors but overall is high classification accuracy. Figures 5 demonstrate a characteristic delayed learning curve, in which accuracy levels off at 20% for 40 epochs before rapidly increasing to 90%, and eventually stabilizing at 95% with strong diagonal confusion matrix values, ultimately reaching comparable final performance.

B. *ROC Curve Analysis*

The model capability of separate classes are measured through ROC curves. In this article compares two deep networks InceptionResNetV2 and Resnet50 for binary and multi-class classification.

Fig. 6. a) ROC curve of



InceptionresnetV2 with two classifications

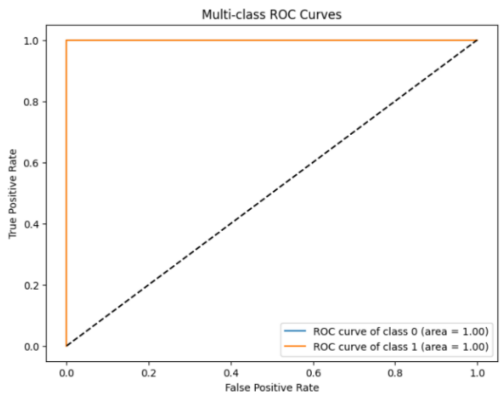


Fig. 6. b) Resnet50's ROC curve with two classifications

Figure 6a. shows the ROC curve of InceptionResNetV2 for binary classification. Highly close to the top-left area, the curve illustrates the balance between true positive rate and false positive rate. The value of AUC for this plot is 1.00, which means a perfect model performance where both classes are completely separated with no classification errors. Figure 6b. As in the above figure for InceptionResNetV2, the ROC curve of ResNet50 on the same binary classification task with an AUC value of 1.00, completely follows the ideal path of ROC curve. This means that ResNet50 has the same performance as InceptionResNetV2, making no mistakes at all in discriminating between the two classes.

The comparison of ROC curves and AUC values from different models and tasks indicates that InceptionResNetV2 and ResNet50 are well-performing on both binary and multi-class classification tasks.

Binary Classification Task

- InceptionResNetV2 had an AUC value of 1.00, implying perfect separation of the two classes.

- ResNet50 had an AUC value of 1.00, perfect to distinguish the two classes with no errors.

- They differed but still not very different in AUC, in that most of the values in some models had an AUC value of 1.00. The ROC curves and AUC values provided in the results describe how the InceptionResNetV2 and ResNet50 models are extremely potent for classifying skin diseases. Notable outcomes from the classifications, whether they are binary or multi-class classifications, serve as a testimony to the success these models hold while diagnosing and detecting several skin diseases.

In Figure 7, comparison on proposed work based on detection of skin diseases named Psoriasis, Eczema with different networks named MobileNet, Inception V3, Densenet, Inception50 etc. with 3 classifications. On the basis of information received the following graph be plotted. Numerous researchers had proposed different skin disease detecting methods. Statistical comparison between various works and the solution proposed is given in Table II. With the results obtained in Table III, one can observe, because various skin disease involves varying colors and forms that most of the works stressed on feature choice and texture choice process.

And the majority of the CNN solutions achieved a comparable level of accuracy. The following observations are derived from the experimental study of the skin disease dataset:

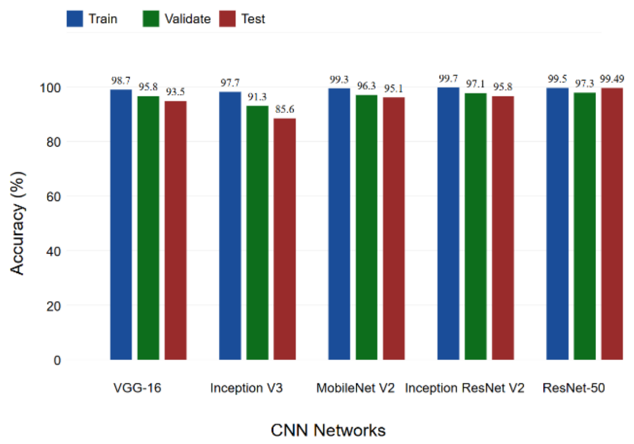


Fig. 7. Comparison of Proposed work with other networks

TABLE III
COMPARISON OF PROPOSED MODEL WITH EXISTING WORK

Authors	No.of Disease	Proposed method	Performance (%)
Abbadi[3]	1 (psoriasis)	GLCM feature extraction with feed forward neural network	All samples are detected correctly
Srivastava [5]	1 (eczema)	Neural Network model.	Accuracy = 90%
Bhadula [9]	3 (lichen planus, acne, sjs-ten)	Machine learning classifiers-based approach	96% accuracy on testing dataset
Shanthi[10]	4 (Acne, Keratosis, Eczema, Urticaria)	CNN based classification approach	Accuracy:98.6–99.04%
Goceri [18]	8 Skin diseases	MobileNet	Accuracy=94.7 Precision=90.6 F1-score=91.3
Proposed model	2 (eczema, psoriasis)	Resnet50 Architecture with Adam Optimizer	Accuracy=**99.4** Precision=1.0 Recall=1.0 F1-Score=1.0

Any CNN model's accuracy on a given dataset is greatly increased using the transfer learning technique. The Adam optimizer completed the categorization operation more quickly in terms of execution time. Highest training, validation, and test accuracy were achieved by ResNet50 and Inception ResnetV2 models with Adam optimizer. Adam optimizer can be utilized for classification task based on accuracy. Over-fitting behaviors are exhibited by ResNet-50 architectures with Adam optimizer. Inception ResnetV2 shows improved performance compared to its hybrid architecture. Improved weight updation is achieved using learning rate 0.0001 and momentum 0.9. 0.01 and 0.001 learning rate also worked equally well.

CONCLUSION

This study focused on the development of deep learning techniques for identifying the three most prevalent skin conditions: eczema, psoriasis, and cancer. To create a precise and reliable automated diagnosis system for skin conditions, Employed various Convolutional Neural Network (CNN) architectures. Our investigation revealed that the ResNet50 architecture, combined with transfer learning and the Adam optimizer, outperformed previous CNN models. This configuration had achieved a testing accuracy and training accuracy of 99.49% and 99.9%, respectively. Demonstrating that the potential of deep learning in transforming dermatological diagnostics. The effective deployment of such a system has significant implications for healthcare. Early and accurate diagnosis of skin diseases will substantially improve patient outcomes and enable timely interventions. This technology will also enable healthcare professionals to focus on more complex cases, making quality healthcare more accessible, particularly in regions with limited dermatology expertise. While this study represents a significant advancement, further research is necessary to develop and extend deep learning-based skin disease detection. Future studies should investigate the inclusion of a broader range of skin conditions, optimal architectures, and the use of larger and more diverse datasets. These efforts will likely lead to improvements in accuracy, robustness, and clinical utility, ultimately enhancing the diagnosis and treatment of skin diseases.

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