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Skin Disease Detection Using Machine Learning

Dr. T. Kameswara Rao[1], Professor, Department of CSE,
Vasireddy Venkatadri Institute of Technology, Nambur, Guntur Dt., Andhra Pradesh.
P. Chamanthi[2], **N. Tharun Kumar**[3], **R. Lakshmi Amulya**[4], **M. Uday Sagar**[5]
[2,3,4,5] UG Students, Department of CSE,
Vasireddy Venkatadri Institute of Technology, Nambur, Guntur Dt., Andhra Pradesh.
E-Mail ID's: tkr.cse@vvit.net[1],
chamanthipaineni@gmailcom[2], tharunkumarnalabothu@gmail.com[3] ,
amulyaramineni2002@gmail.com[4], udaysagarmeka@gmail.com[5]

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Abstract

Many people face a lot of problems with their skin. Many are suffering from various skin diseases, which have always been a common complication in humans. Traditional treatments for diagnosing skin problems require a lot of tests and the diagnosis is seen to be time-consuming and requires an extensive understanding of the domain. Visual assessment in combination with clinical information can be helpful for the diagnosis. The approach involves the development using Convolutional Neural Networks (CNN) and an ensemble model using VGG16, DenseNet and Inception. Specific skin diseases namely Actinic Keratoses, Basal Cell Carcinoma, Benign Keratosis, Dermatofibroma, Melanoma, Melanocytic Nevi and Vascular Lesions are considered. Results show that using CNN, the accuracy ranges from 71%-75%, VGG16 has attained an accuracy of 80.3%, DenseNet with 82.3%, Inception with 80.4% and an ensemble of VGG16, DenseNet and Inception has achieved an accuracy of 83%-85%.

Keywords: Convolutional Neural Network, DenseNet, Ensemble Learning, Inception, Skin disease and VGG16.

Introduction

Skin conditions are prevalent and can impact individuals of all ages, genders, and ethnicities. The World Health Organization reports that approximately 900 million people worldwide are currently affected by skin diseases. Skin conditions impact the appearance, texture, and functioning of the skin. They can range from mild afflictions to serious and potentially fatal diseases like skin cancer.

Skin diseases can be caused by a variety of factors, including genetic predispositions, environmental factors, infections, autoimmune disorders, and allergies. It's crucial to seek medical attention if there are any changes in the skin's appearance or unusual symptoms occur.

Moreover, Machine Learning has quickly evolved into the method of choice for analyzing medical images. CNN is currently among the most popular and illustrative deep learning models. It has been extensively used in a variety of medical image analysis applications, and medical image classification.

Literature Survey

Several research papers were published on detection of various skin diseases. Some of the papers that were considered for the understanding are mentioned below.

In the publication "Diagnosis of skin diseases using Convolutional Neural Networks" by Jainesh Rathod et al. [1], the authors created a web application using CNN and softmax as a classifier. The model attained an accuracy of approximately 70%.

In "CURETO: Skin Diseases Detection Using Image Processing and CNN" by R.K.M.S.K. Karunanayake et al. [2], a mobile application using CNN for the detection of skin diseases is built. A custom sequential CNN model attained an accuracy of 79.55%. The authors indicated their future plans to suggest dermatologists based on the model's output.

In "Skin lesion classification using convolutional neural networks" by Tareq Tayeh et al. [3], various CNN models including InceptionV3, ResNet152V2, VGG16, and TSM12, were used to build the model. The performance of each model was compared and ResNet152V2 and VGG16 achieved the highest accuracies of 82.14% and 88.54%, respectively.

The model discussed in "Derm-NN: Skin Diseases Detection Using Convolutional Neural Network" by Tanzina Afroz Rimi et al. [4] was designed to detect several skin diseases using CNN. The accuracy attained was approximately 73%.

In "Skin Diseases Prediction using Deep Learning Framework" by Padmavathi S et al. [5], authors have designed the model using CNN and ResNet. The output model will be used to make the predictions for the required data. The accuracy of the model using CNN is 77% and using RestNet is 68%.

In "Skin Disease Detection using Machine Learning" by Kritika Sujay Rao et al. [6], the researchers implemented CNN using the Keras Sequential API. 93.35% accuracy has been found for the developed model. It is concluded that the trained model may function similarly to dermatologists with better models and better data sets.
The authors of "Skin Cancer Detection using VGG-16" by Kanneboina Manasa et al. [7] employed VGG-16 and ResNet-50 for skin cancer detection. These models achieved 80% and 87% accuracy, respectively. The conclusion drawn was that using CNN architecture like VGG-16 and ResNet50 can result in an accuracy of approximately 80%.

ISSN PRINT 2319 1775 Online 2320 7876

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The publication "Detection and Classification of Skin Diseases using Deep Learning" by T. Swapna et al. [8] details the use of three pre-trained CNN models, ResNet, InceptionV3, and AlexNet, to identify skin conditions. ResNet achieved the highest accuracy score of 88.83% among the three models.

In "Automatic skin disease diagnosis using deep learning" by K.A. Muhaba et al. [9], the authors designed a smartphone application to predict skin disease using a pre- trained mobilenet-v2 model. An accuracy of 97.5%, has been achieved.

The work of "Skin Disease Detection Using Deep Learning" by Sruthi Chintalapudi et al. [10], aimed to develop a user-friendly portal to upload images and get results. The system was developed using the CNN model. The accuracy obtained for the developed model is around 90%.

The authors of "Skin disease Detection using Convolutional Neural Network" by Srujan S et al. [11] have developed using the CNN approach. The precision was between 74% and 75%. It is concluded that accuracy could be improved by selecting a suitable dataset.

In "Detection and classification of skin diseases with ensembles of deep learning networks in medical imaging" by A. Kalaivani et al. [12], the authors have used the ensemble classifier named Random Forest Deep Convolutional Neural Network and Classical CNN. The Random Forest technique and Convolutional Neural Networks are combined to form a model. The accuracy obtained by classical CNN model was 88% and by RF-DCNN is 90%.

The thought of using CNN model and ensemble model using VGG16, DenseNet, and Inception was raised after studying the above papers. A total of five models are built: a basic CNN, VGG16, DenseNet, Inception and an ensemble model.

Problem Identification

Skin disease detection has been a major challenge for dermatologists for decades. However, the development of new technologies has made it possible to develop systems for skin disease detection.

The proposed system consists of five models developed namely, CNN, VGG16, DenseNet, Inception model and ensemble of VGG16, Inceptionv3 and DenseNet models to detect the skin disease using the dermatoscopic images of the affected area of skin. The system was used to predict seven skin diseases namely Actinic Keratoses, Basal Cell Carcinoma, Benign Keratosis, Dermatofibroma, Melanoma, Melanocytic Nevi and Vascular Lesions.

The HAM10000 dataset, a huge collection of dermatoscopic images of typical pigmented skin lesions, was the data set used to create our model.

ISSN PRINT 2319 1775 Online 2320 7876

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The CNN model is a deep learning algorithm that uses a set of convolutional layers to learn features from input data. It is a powerful tool for image classification, object detection, and segmentation. VGG16, DenseNet and Inception are the pretrained models that are available in keras or tensorflow. By making suitable changes to these pretrained models, they can be used.

The ensemble of VGG16, InceptionV3, and DenseNet models uses a combination of models to improve the accuracy and robustness of skin disease detection. This model combines the strengths of three different architectures viz VGG16, InceptionV3, and DenseNet.

Based on the accuracies obtained by the proposed models, the model with higher accuracy is used for the detection of skin disease. The accuracy of systems for skin disease detection depends on various factors, including the quality of the image data, the complexity of the skin disease, and the algorithm or model used for analysis.

Methodology

The model is executed in a series of steps.

1. Data Gathering: HAM10000 dataset is collected from dataverse.harvard.edu.

2. Data Transformation: It includes transferring data from one format into another. The dataset consists of images and those are converted into pixels by using Python Image Library to extract features from images and to classify them.

3. Data Augmentation: Augment the dataset by applying random transformations such as rotation, zooming, flipping, and shifting to increase the diversity of the dataset. The HAM10000 dataset consists of an uncertain number of images for each disease, so to maintain equality in the dataset Random Over Sampler is used.

4. Splitting Dataset: First, divide the dataset into features and labels. The data frame is divided training and testing sets which are used to train and test the model.

5. Model Building: A CNN model is created by adding several layers in a sequential manner. In the proposed CNN model 22 layers are added among them 5 layers are convolution layers, 2 are pooling layers, 5 dense layers, 6 batch normalization layers, 3 dropout layers and one flatten layer. On the other hand, select VGG16, InceptionV3, and DenseNet architectures as base models for the ensemble and load those pre-trained models and make changes as required.

6. Model Training: Train all models CNN, VGG16, Inceptionv3 and DenseNet with the train set by specifying batch size and number of epochs.

7. Ensemble of Models: Create an ensemble of models, such as VGG16, InceptionV3, and DenseNet, and combine the predictions by using an average method.

8. Model Evaluation: Evaluate the performance of the models using standard evaluation metrics.

ISSN PRINT 2319 1775 Online 2320 7876

Research paper UGC CARE Listed (Group -I) Journal Volume 11, Iss 12, Dec 2022

9. Comparison of Models: Compare the performance of all the models and analyse the performance.

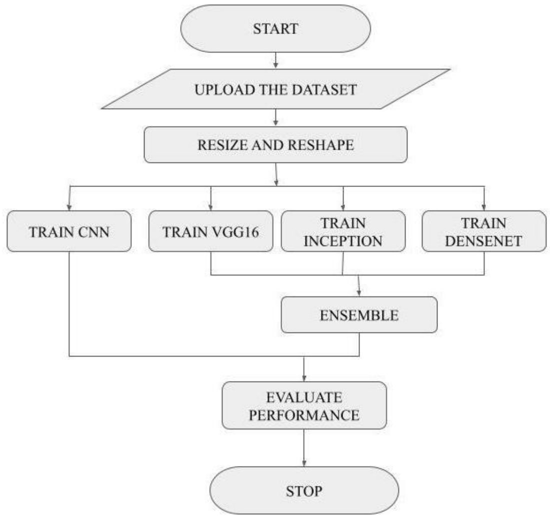

Fig. 1: Flowchart

Fig. 1 represents the flowchart through which the model is created.

Initially the dataset is uploaded. The images are resized and then used for the development of the model. The images are converted into pixels and used for the development. CNN, VGG16, DenseNet and Inception models are developed.

An ensemble model [14-31] is created by combining VGG16, Inception and DenseNet. After the development of all the models, the performances are evaluated and compared.

Implementation

The first step is to collect a large dataset of skin images, labeled with the corresponding skin conditions. After collecting the data, preprocessing is to be done by resizing the images to a fixed size, normalizing the pixel values.

The next step is to train individual CNN models on the training set. Transfer learning can be used to train the models faster and in an efficient way. It involves taking a pre-trained model and fine-tuning it for the specific task. VGG16, InceptionV3, and DenseNet have been pre-trained on the ImageNet dataset. Final fully connected layer is to be replaced with a new layer.

After training the individual CNN models, Ensemble of the models is created to improve the performance of the system. The classifier of the ensemble model calculates the average of the predictions of the individual models. Metrics like accuracy can be used to evaluate the performance of the model.

ISSN PRINT 2319 1775 Online 2320 7876

Research paper UGC CARE Listed (Group -I) Journal Volume 11, Iss 12, Dec 2022

A. CNN

Convolutional Neural Networks are multilayered neural networks with a distinctive architecture for detecting complex features in input. CNNs have been used in a variety of applications, including image identification, robotic vision, and self-driving vehicles. The basic CNN architecture is represented in Fig. 2.

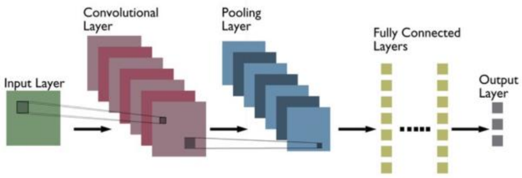

Fig. 2: Basic CNN Architecture

(Courtesy: www.vitalflux.com)

The basic CNN model comprises three main layers: Convolutional layer, Pooling layer and Fully connected layer.

Convolutional Layer: It is the most important layer of CNN. Convolutional layers are made up of filters that are applied to an input image. In this layer, the dot product between an image's pixel matrix and kernel is calculated. The output is known as a feature map.

Pooling Layer: Almost always, it occurs after a convolutional layer. The reduction in size of the convolved feature map is the major goal of this layer. Max Pooling uses the feature map to determine which element is larger. The average of the elements in a section of an image of a certain size is calculated in average pooling.

Fully Connected Layer: All of the neurons in the layer above and below it are fully connected to those in this layer. The mapping of the representation between the input and output is facilitated by the FC layer. The FC layer receives flattened input from the preceding levels. The flattened vector is subsequently passed through a couple more FC levels. It is the point where classification occurs.

B. VGG16

The Visual Geometry Group at the University of Oxford created VGG16 (Visual Geometry Group 16), a deep convolutional neural network architecture, in 2014. For tasks involving picture categorization, it is one of the most frequently used deep learning models. The VGG16 network contains 16 layers, including 13 convolutional layers, three completely linked layers, and so on, as shown in Fig. 3. The convolutional layers are responsible for extracting information from the input image, and each layer that follows learns increasingly complex features.

ISSN PRINT 2319 1775 Online 2320 7876

Research paper UGC CARE Listed (Group -I) Journal Volume 11, Iss 12, Dec 2022

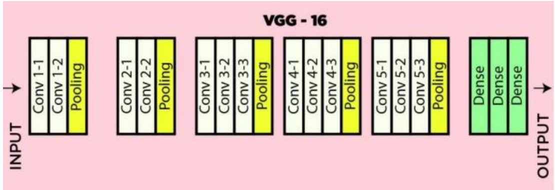

Fig. 3: VGG-16 Architecture
(Courtesy: www.geeksforgeeks.org)

The classification of the collected characteristics is carried out by the three fully linked layers at the network's end. A softmax layer that outputs the probability for each class makes up the final output layer.VGG16 is still widely used for transfer learning, which uses previously trained models as a starting point for training on new tasks or datasets.

C. DenseNet

The main concept of DenseNet is to feed-forward connection to every other layer, creating a dense network. The architecture is formed by a number of dense blocks, each of which is composed of a number of convolutional layers that are closely coupled to one another. Dense blocks are necessary for the model to function. The output of every layer in a dense block is combined with the output of all preceding layers and provided as an input to the following layer in the block, as shown in Fig. 4. As a result, a highly connected network is created, enabling easier information flow and improved feature reuse.

Densenet is divided into dense blocks where the number of filters is different, but the dimensions are the same. Every layer takes additional input from every layer that came prior to it and transmits its feature maps to every layer that comes after it.

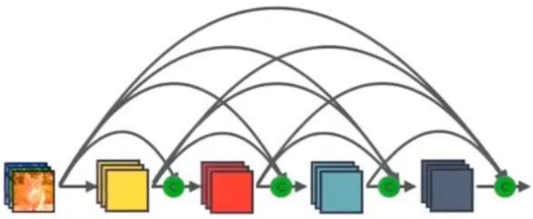

Fig. 4: Main Idea of DenseNet

(Courtesy: www.towardsdatascience.com)

The architecture of the DenseNet contains Dense blocks connected with Transition blocks as shown in Fig. 5. A convolutional layer with a small kernel size is applied to the input image to create the initial feature mappings. The first dense block, which consists of a collection of convolutional layers that form feature maps, receives the initial feature maps. Each layer's output is combined with the output of all earlier layers in the block to create a feature map and then passed on to the next block.

ISSN PRINT 2319 1775 Online 2320 7876

Research paper UGC CARE Listed (Group -I) Journal Volume 11, Iss 12, Dec 2022

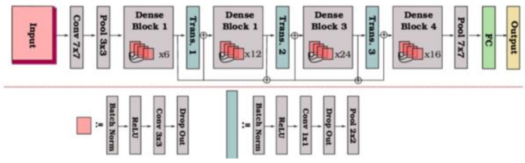

Fig. 5: DenseNet Architecture
(Courtesy: www.pluralsight.com)

A transition layer is implemented in between dense blocks to reduce the feature maps and spatial dimensions. The transition layer is composed of a batch normalization layer, a 1x1 convolutional layer, and a 2x2 average pooling layer. A global average pooling layer, the top layer of the network, calculates the average of each feature map over all of its spatial dimensions. A fully linked layer using softmax activation receives the output vector for classification.

D. Inception

InceptionV3 is a convolutional neural network architecture that was developed by researchers at Google in 2015. It has 48 layers. The "V3" in the name stands for version 3. Convolutions of sizes 1x1, 3x3, and 5x5 are combined with pooling and normalization layers in Inceptionv3. The inception modules contain layers that carry out several convolutions at various scales and combine the outputs.

In Fig. 6, the Inception module is depicted. This enables the network to learn features at various scales and gather data at various levels of detail. The network's final layers typically consist of a fully connected layer, a global average pooling layer, and a softmax activation function to provide class probabilities.

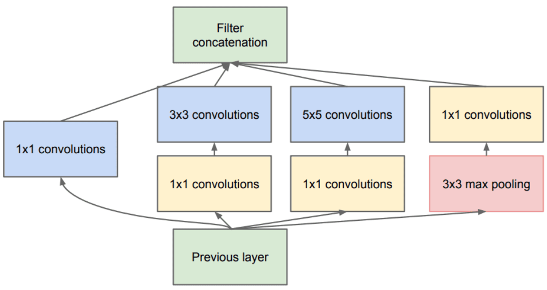

Fig. 6: Inception Block
(Courtesy: www.iq.opengenus.com)

E. Ensemble Model

Ensemble learning is a machine learning technique that involves combining multiple models to improve the overall performance of the system. The basic idea is to train several models on the same dataset, and then combine the predictions to make a final decision. The primary principle behind ensembling is that by integrating the predictions of various

ISSN PRINT 2319 1775 Online 2320 7876

Research paper UGC CARE Listed (Group -I) Journal Volume 11, Iss 12, Dec 2022

models, the ensemble can capture the collective knowledge of the different models and generate a stronger and more precise forecast. Fig. 7 helps us to understand this idea.

Ensemble learning is very helpful in scenarios where various strengths and weaknesses of separate models may exist. Because it uses each architecture's benefits while minimizing the impact of its limitations, assembling multiple architectures can result in superior performance than any individual model.

For example, VGG16 has strong feature extraction capabilities, while Inception V3 and DenseNet can better capture spatial relationships between image features. Combining these architectures can help improve the overall accuracy and robustness of the image classification system.

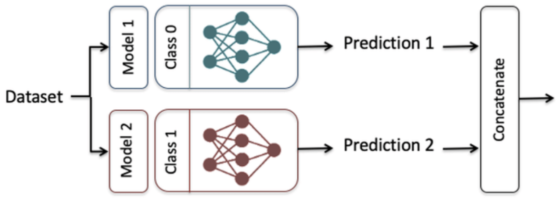

Fig.7: Ensemble Learning

Results

The below table shows the accuracies obtained by each model. Based on the comparison of the performances, the ensemble model which is developed using VGG16, DenseNet and Inception has attained highest accuracy of 85.02%.

S. No	Model	Accuracy %
1	CNN	74.59
2	VGG16	80.33
3	DenseNet	82.83
4	Inception	80.43
5	Ensemble model	85.02

Conclusion

The ensemble model has shown an improved performance compared to the individual CNN models, suggesting that combining different architectures can be an effective way to improve accuracy. This project detects only 7 types of skin diseases and has important implications for healthcare and accurate diagnosis of skin diseases is crucial for effective treatment and prevention of further spread. However, it is important to note that the models are only predictive and should not be used as a substitute for medical advice by a doctor.

ISSN PRINT 2319 1775 Online 2320 7876

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Limitations & Future Scope

One of the limitations of this project is the availability of a diverse and large dataset of skin diseases. Depending on the quality and quantity of the dataset used, the accuracy of the machine learning models may be limited. Another limitation is that, if the input image contains more than one disease, conflict occurs and it only detects a single disease and if a no disease skin is given it cannot function in that way since no disease case is not included for the system. It is limited to detecting only 7 specific skin diseases. If the input is given from any other disease type, it fails to detect.

In the future, there is an opportunity to integrate skin disease detection using machine learning models into telemedicine platforms. This could provide patients with an initial diagnosis before they visit a doctor in person. A better dataset can be used to improve the accuracy of the machine learning models. This project focused on a specific set of skin diseases, but there is an opportunity to expand the number of skin diseases that the machine learning models can detect accurately. This could be done by adding more images to the dataset and training the models on these images.

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