PERFORMANCE ANALYSIS OF CLASSICAL CNN BASED MODEL VERSUS RF-DCNN CLASSIFIER MODEL

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Abstract
The most important element of the human body is the skin. The skin preserves the body from UV rays, illnesses, wounds, temperature, and damaging radiation, as well as aiding in vitamin D3. Because the skin is so vital in managing core temperature and protecting the body from skin disorders, it's important to keep it healthy. Skin disorders may appear harmless, yet they can be dangerous if not treated properly. Many diseases have early symptoms, but most of them are identical, making it difficult to diagnose the condition at an initial point. Skin disorders cause not only physical but also psychiatric disorders, particularly in individuals whose faces have been scarred or deformed. Skin can be influenced by a range of external and internal factors.

Keywords:
Classification, Mining, Computational, Machine Learning and Deep Learning

Introduction

Artificial skin injury, severe chemical causes, adversity illnesses, a person's immunity, and genetic anomalies are some of the factors that influence skin disorders. Skin diseases have a big influence on people's lives including well. Dermatological illnesses are the most challenging subfields of science to cure because of the complications in treating symptoms and how symptoms alter in various situations. Skin diseases are frequent among many illnesses, and if these tactics are not fit for that form of skin condition, it will cause negative effects. People are frequently infected by skin illnesses, which must be treated as soon as possible.

Problem Statement

This research work addresses the problem of abnormalities detection in skin lesion images. It endeavors to develop efficient and robust approaches for the non-invasive detection of anomalies. The main indications of structured and unstructured skincare data using Ensemble Machine Learning (ML) and Deep Learning (DL) techniques are discussed for skincare Data Analysis. These approaches follow a framework of image processing with the following phases as pre-processing, segmentation, feature extraction, and classification of skin lesion images.

Challenges in skin lesion analysis

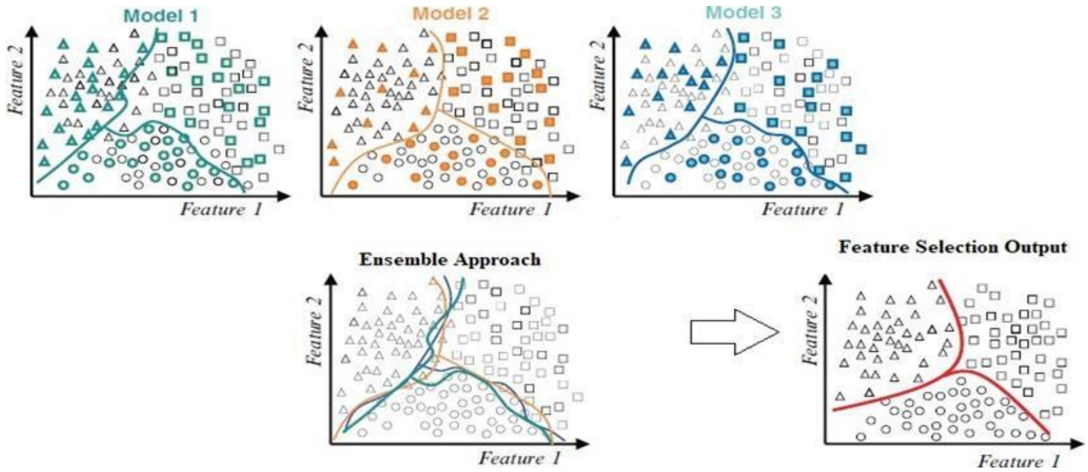
Empirical examinations illustrate that people having no medical guidance and no exact education about dermatology are able to group the images of a skin lesion into consistent classes or sub-classes. This sign advocates that some inherent visual features which can serve as guidance in the task of classification. The machine learning approaches can be used to extract these features from the visual classes using image processing and finally establish an automated system.

Challenges for early detection of skin lesions

Existence of blood vessels on a stretch of skin can be easily recognized by a viewer. But as long as there is variability in its pattern and the presence of “discontinuities” (e.g. visible patterns of skin and hairy region), it is difficult to detect them by computer vision approach in automated systems.
Diagnostic criteria like as the ABCD rule does not reflect any knowledge of medical system used by dermatologists during the diagnosis.
An important issue for lay people is the visual system design, and human perception to perceive skin lesion. The difficulties arise in identifying the multiple-color shades of each lesion. For, discriminating the color shades, human inspired visual models are adopted. This phenomenon identically happens in

skin lesion images for skin lesions color patterns, and it has a lot of implications for pigmented skin lesion screening.
High-performance systems in the domain of dermatology using image processing methods require fast and robust computation.

Ensemble Machine Learning and Deep Learning for Data Analysis
Electronic Healthcare Records (EHR) consists of patients health related information collected from hospitals, healthcare centers, lab tests, etc. Representing this kind of data is available in structured and unstructured format. Considering this data, early disease diagnosis is possible, which can prevent severe skincare problems and reduce mortality rates. Machine Learning (ML) plays a vital role in creating useful insights from healthcare data. Skin disease classification with existing data is also an important problem in the healthcare sector. ML is also used to extract healthcare knowledge by applying innovative methods to improve classification performance. These classification models can improve patient care by enhancing the model decision. Recent studies have proved that classification using a single model obtains less classification accuracy compared to combined model classification. These combinations of multiple models are termed as Ensemble Learning (EL). The advantage of the ensemble is that it is a combination of the best models which perform well compared to the individual classifiers.

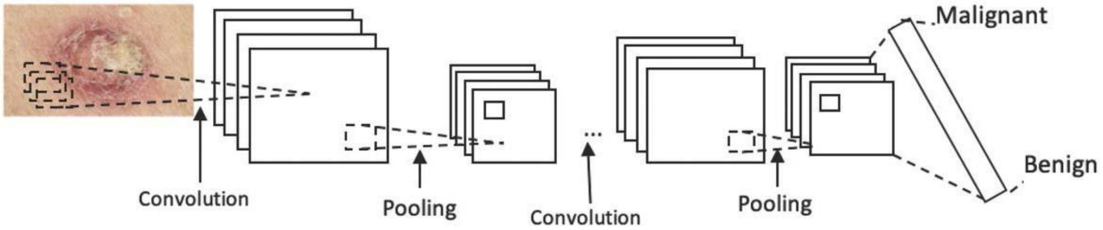


Representation of Feature Selection using Ensemble Approach

Likewise, when the dimensionality of data increases, them a in preprocessing tool applied is feature selection. The combination of different feature selection models significantly improves the ability to select appropriate features without degrading the classification performance. It is proved that ensemble feature selection performs more effectively than a single selector. The flow of ensemble feature selection is represented in Figure. A similar kind of approach is carried out for ensemble classification also. There are several ensemble methods used for ensemble for analyzing structured and unstructured data.
The co-operative ensemble classification is a combination of classifiers where all the classifiers will make some contribution to the final EL model. Averaging classifiers, weighted averaging classifiers, and stack generalization classifiers are examples of co-operative ensemble classifier techniques. In addition, competitive ensemble classification chooses the most appropriate classifiers among several classifiers.
The two main approaches to competitive learning are:
Gating: It works on the concept of divide and conquer, that is, breaking complex problems into small problems to solve them easily.
Rule–based switching: Certain conditions are applied to the model.

Convolution models in melanoma diagnosis
In the following, a general description about the CNN and how to optimize them will be described.
In simple words, CNNs are a type of feed-forward neural network that uses a mathematical convolution operation to extract features from images automatically. These features are passed to successive layers

that learn more abstract features from previous ones until a final output is yielded, simulating some of the human visual cortex. Consequently, CNNs can build more complex concepts from simpler ones, e.g., they can learn to detect a human face based on more straightforward ideas as a nose and mouth, which are known from much simpler ones such as corners and contours. As a matter of example, Figure illustrates a simple CNN model that learns to predict whether or not a patient has melanoma utilizing mapping the extracted features into more abstract feature spaces. The general layout of CNN architecture is significant, including layers, activation function, and hyper-parameters. Layers in CNN are mainly categorized into convolution, pooling, and fully connected layers. An activation function is a transformation function that maps the input signals into output signals required for the neural network to function. Popular activation functions include linear activation, Sigmoid functions (logistic and hyperbolic tangent functions), Rectified linear units (ReLU), also known as piecewise linear functions, Exponential Linear Unit, and Softmax. Hyper-parameters include filter kernel, batch size, padding, learning rate, and optimizers, etc. Optimizers are used to produce maximum performance from a network model. Examples include Adam, Rmsprop, Nesterov, and Sobolev gradient based optimizer.



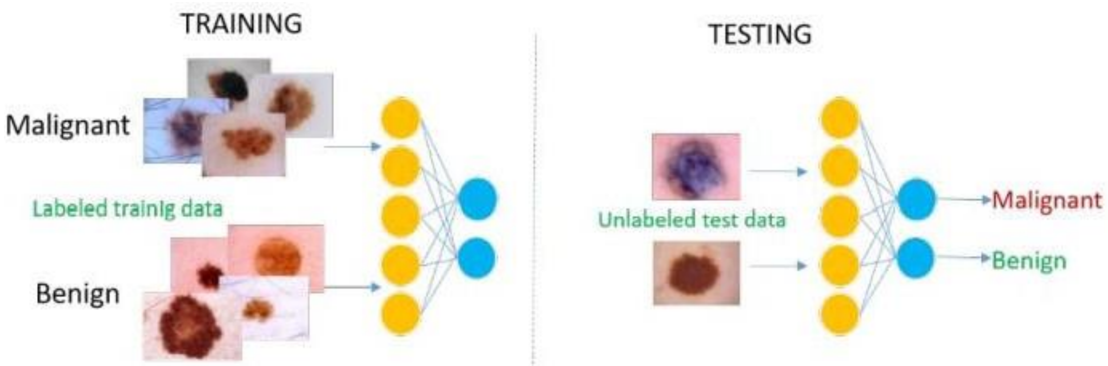
Diagnosis of melanoma with a simple CNN model

CNN architectures

There are various architectures of CNNs available. These architectures are critical factors in building deep learning algorithms. Here, we present a brief review of these classic CNN models, including AlexNet, VGG architecture, Inception architecture, ResNet architecture, DenseNet architecture, Xception architecture, MobileNet architecture, NASNet architecture, and EfficientNet architecture, ect. more than a hundred CNN models.

Classification of Lesion Classification

Skin lesion images can be classified to facilitate the process of detecting melanoma cancer. Several forms of skin cancer can be seen from the skin lesions images. These can be categorized majorly into malignant and benign. They can further be classified into more lesion classes. Melanoma is a malignant lesion and the most deadly of these classes. The image classification involves using selected features of an image to classify the image's pixels into one of the several classes relying on a specific knowledge domain. It could be training a model using a data set and then testing it using one disjoint data set from the training. Most lesion classifications are binary, classifying between malignant and benign moles. The results of classification are typically influenced by the chosen feature descriptors and the classifier's strength. The automated classification performance is equally dependent on the degree of dataset population.



Classification model of melanoma.

The two main classification types reported in the paper concerning medical imaging are supervised classification and unsupervised classification. Supervised classification uses an image analysis tool to generate a statistical categorization (such as mean and covariance) of each identified information class's reflectance. Completing the categorization then fosters effective classification by examining each pixel's reflectance and deciding on the best matching signatures. Decision criteria such as maximum likelihood can be used for overlapping signatures to assign pixels to the highest probable class. Unsupervised classification typically examines many unknown pixels and divides them into several categories based on natural groupings present in the image values using clustering procedures. Essentially, unsupervised classification clusters values that are close together in a measurement space as a single class, thus arranging the data in various categories to be comparatively separated. Sample DL application for lesion classification purposes can be seen in multiple studies.

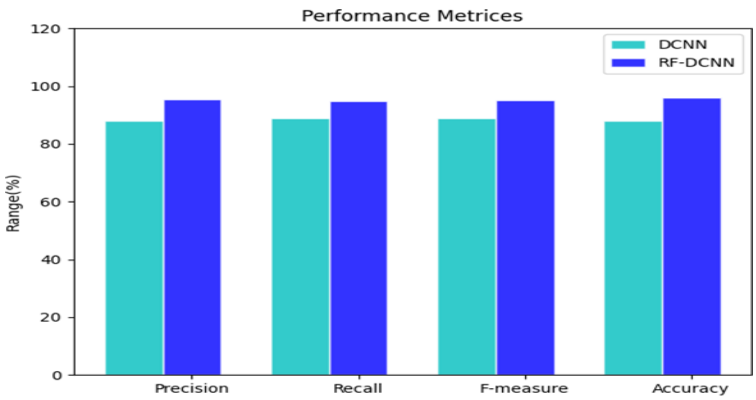
Algorithm for RF-DCNN Classifier

Input: HAM 10,000 image dataset
Output: classified into different skin disorder classes
Begin
To extract multi-level features, map the features of skin visuals from the input domain (HAM10000) to the ensemble deep neural network (RF-DCNN);
Get the multi-level distinctive features that were extracted;
$\boldsymbol{for}(each\ input\ skin\ image)$
Train the RF-DCNN from start to the end;
Get the skin visuals with the two-step feature extracted;
Provide the RF-based DCNN classifier with the features extracted skin data;
Sort the various types of skin conditions into categories;
$\boldsymbol{endfor}$
End

The ensemble technique is more accurate and effective at predicting skin diseases. Table shows how individual deep learners from classic CNN compare to the proposed ensemble classifier in terms of classification performance. Chart shows the performance of the conventional Learning model rather than the newly presented model.

Performance analysis with traditional deep learning-based models

Performance for various metrics	Classical CNN based Model	RF-DCNN Classifier model
Precision %	**88**	**95.41**
Recall %	**89**	**94.93**
F-measure %	**89**	**95.17**
Accuracy %	**88**	**96.1**



Effectiveness of Performance Metrics on RF-DCNN and CNN based Models

The integration model enhanced some of older CNN models with mean-accuracy, precision, f1-score and re-call, as shown in the table. Performance evaluation criteria such as accuracy, sensitivity, and specifcity may be used to compare skin lesion segmentation and classification performance. We identified various state-of-the-art methodologies for performance comparison in this research, and the results are displayed in Table below. In this comparison, words like true positive (TP), false positive (FP), true negative (TN), and false negative (FN) are commonly employed (FN). Since the layers are maintained and imported from a previously trained network. The study uses two separate classification methods: the random forest Classifier and the Deep Convolution Neural Networks Classifier. We reached the greatest mean-accuracy of 96.1 percent after using these strategies.

Conclusion

This study aided in the development of a system for forecasting skin disorders. Finally, in the healthcare business, data mining is crucial. In this work, integrated Predictive heterogeneous ensemble models that work well for multiclass dermatitis are developed using a number of simple and weight-bearing rules. The results acquired in this study were compared to other data found in the literature to demonstrate the effectiveness of our technique. We used a large number of technical studies using the same information but various classification techniques to compare the efficiency of the proposed treatment of skin classification, and then developed a multi-model ensemble method to compare the efficiency of the proposed treatment of skin classification. After that, we use a multi-model ensemble approach to combine these two data mining techniques to get the greatest accuracy of 96.1 percent. On the skin illness dataset, we achieve the greatest accuracy in the literature.

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