International Journal for Modern Trends in Science and Technology, 8(09): 295-301, 2022

ISSN: 2455-3778 online
DOI: https://doi.org/10.46501/IJMTST0809055
Available online at: http://www.ijmtst.com/vol8issue09.html

Detection of Skin Diseases using Ensemble Machine Learning Approach

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To Cite this Article
M Sree Ram Kiran Nag . Detection of Skin Diseases using Ensemble Machine Learning Approach. International Journal for Modern Trends in Science and Technology 2022, 8(09), pp. 295-301. https://doi.org/10.46501/IJMTST0809055

Article Info
Received: 02 September 2022; Accepted: 20 September 2022; Published: 25 September 2022.

ABSTRACT

Skin diseases are a common and wide-ranging health issue that affects millions of people worldwide. Early and accurate diagnosis of these conditions is crucial for effective treatment. Machine learning techniques have shown great promise in automating the process of skin disease detection, offering the potential to improve diagnosis speed and accuracy. This study focuses on the application of an ensemble machine-learning approach for the detection of skin diseases. The proposed ensemble approach combines the strengths of multiple machine learning algorithms, including Decision Trees, Random Forests, Support Vector Machines, and Convolutional Neural Networks (CNNs). By leveraging the diverse capabilities of these algorithms, we aim to enhance the overall performance of skin disease detection. The dataset used in this study comprises a comprehensive collection of dermatological images, including various common skin conditions such as eczema, psoriasis, melanoma, and acne. Embodiment preprocessing techniques are employed to standardize and enhance image quality. The ensemble model is designed to take advantage of both image-based and feature-based information for robust classification. The evaluation of the ensemble model's performance is carried out using standard metrics such as accuracy, precision, recall, and F1-score. The results demonstrate the superiority of the ensemble approach in comparison to individual algorithms, showcasing its potential to improve the diagnostic accuracy of skin diseases. Furthermore, the model is also compared to the performance of dermatologists to assess its practical utility. Finally, this research proposes an ensemble machine learning approach for the detection of skin diseases, which has the potential to provide accurate and timely diagnosis, benefiting both patients and healthcare providers. The combination of various machine learning algorithms, image preprocessing, and a diverse dataset contribute to the robustness and reliability of the proposed model. This work paves the way for developing automated skin disease detection systems, which can be deployed in telemedicine and clinical settings to enhance the early diagnosis and management of dermatological conditions.

Keywords: Skin Diseases, Decision Trees, Random Forests, Support Vector Machines.

1. INTRODUCTION

Skin diseases affect millions of people worldwide and can have a significant impact on an individual's quality of life. Early and accurate detection of these diseases is crucial for effective treatment and management [1][2][3]. Machine learning, with its ability to analyze large datasets and extract patterns, has emerged as a powerful tool for the detection of various skin conditions [4][5][6]. Machine learning algorithms can be trained to classify and diagnose skin diseases by analyzing images of the affected skin areas, often outperforming human experts in terms of accuracy and speed. This technology has the potential to revolutionize the field of dermatology by providing more accessible and cost-effective diagnostic solutions [7][8][9][10]. Skin diseases can range from common conditions like acne and eczema to more serious illnesses such as melanoma and psoriasis. Early detection is crucial for effective treatment and prevention of complications [11][12][13]. Traditional methods of skin disease diagnosis often rely on visual inspection by dermatologists, which can be subjective and time-consuming. Biopsies and laboratory tests are used in some cases, but they can be invasive and expensive. Machine learning algorithms, particularly deep learning, can analyze images of skin lesions and make accurate diagnoses. Datasets of labeled skin images are essential for training and evaluating these algorithms.

Figure 1.1: Examples of three types of dermatological images of BCC to show their differences and relationships: (A) Clinical image. (B) Dermoscopy image. (C) Histopathological image

2. LITERATURE SURVEY

Xie et al. [14] proposed a system for classifying skin lesions into benign and malignant categories. The proposed system functioned in three stages. A self-generating NN was used to extract lesions from images in the beginning. The second phase extracted features such as tumor border, texture, and color details. The system removed 57 elements, including seven new features related to lesion border descriptions. Principal component analysis (PCA) was used to reduce the dimensionality of the features, allowing the optimal set of features to be chosen. Finally, lesions were classified using a NN ensemble model in the final phase. Masood et al. [15] proposed an automated skin cancer diagnostic system based on ANNs. This paper also investigated the performance of three ANN learning algorithms: Levenberg-Marquardt (LM) [16], resilient backpropagation (RP) [17], and scaled conjugate gradient (SCG) [18]. When the number of epochs was increased, the LM algorithm achieved the highest specificity score (95.1%). It remained efficient at classifying benign lesions, while the SCG learning algorithm produced better results, scoring a 92.6% sensitivity value. A mole classification system for early melanoma skin cancer detection [19] has been proposed. The proposed system extracted features from lesions using the ABCD rule. ABCD refers to a mole's form, borders, color, and diameter asymmetry. Normal moles are black, cinnamon, or brown, so moles other than those three were classified as melanoma in the proposed system. Melanoma moles commonly have a diameter greater than 6 mm, so that value was used as the diameter threshold for melanoma detection. With 97.51% accuracy, the proposed system used a back-propagation feed-forward ANN to classify moles into three categories: common mole, uncommon mole, or melanoma mole.

Figure 2.1 depicts a proposed automated skin cancer diagnostic system based on backpropagation ANN. For feature extraction, this system used a 2D-wavelet transform technique. The proposed ANN model classified the input images as either cancerous or noncancerous. Choudhari and Biday [21] proposed another ANN-based skin cancer diagnostic system. A maximum entropy thresholding measure was used to segment images. A gray-level co-occurrence matrix (GLCM) was used to extract unique skin lesion features. Finally, with an accuracy of 86.66%, a feed-forward ANN classified the input images as either malignant or benign stages of skin cancer.

3. CONVOLUTIONAL NEURAL NETWORKS (CNNs)

A convolution neural network is a deep neural network widely used in computer vision. It is used to classify images, assemble a set of input images, and recognize images. CNN is an excellent tool for collecting and learning global and local data by combining more specific features, such as curves and edges, to produce more complex characteristics, such as shapes and corners. Convolution, nonlinear pooling, and fully connected layers comprise CNN's hidden layers. CNN can have several convolution layers followed by several thoroughly combined layers. Convolution, pooling, and full-connected layers are the three major types of layers used in CNN.

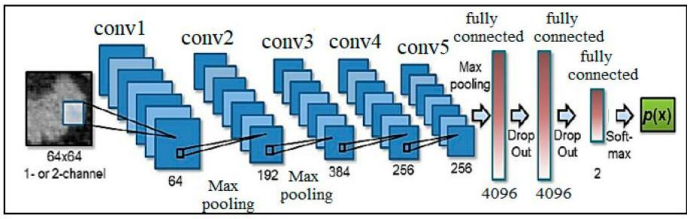


Figure 3.1 CNN Architecture

CNN-based automated deep learning algorithms have demonstrated outstanding performance in medical imaging detection, segmentation, and classification operations—melanoma detection using a deep CNN. A fully convolutional residual network (FCRN) with 16 residual blocks was used in the segmentation process to improve performance. The proposed technique used an average of both SVM and softmax classifiers for classification. It achieved 85.5% melanoma classification accuracy with segmentation and 82.8% without segmentation.

3.1 Implementation

The dataset collected from Challenge 2016 test dataset that contains 379 skin images and 14 attributes belongs to two types of tumors like benign and malignant.

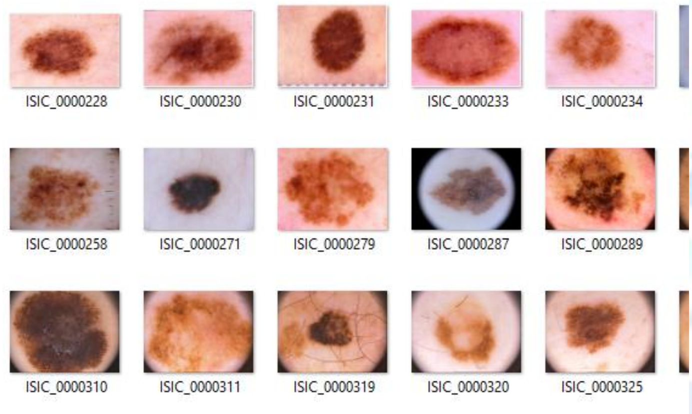


Figure.3.1 input and output images

a) Image Filter

Mean filtering is a basic, instinctive and simple to carry out strategy for smoothing pictures, for example diminishing how much force variety between one pixel and the following. Diminishing commotion in images is frequently utilized. Mean separating is just to supplant every pixel esteem in a picture with the mean ('normal') worth of its neighbors, including itself. This takes out pixel values which are unrepresentative of their environmental factors. Mean separating is normally considered a convolution channel. Like different convolutions it is based around a piece, which addresses the shape and size of the neighborhoods to be inspected while computing the mean.

b) Segmentation

Image segmentation is a technique for dividing an image into different regions or segments based on specific properties or characteristics. Image segmentation can be used to identify and separate cancerous regions from healthy skin regions in the context of skin cancer images. Image segmentation of skin cancer is critical in computer-aided diagnosis and treatment planning. It enables doctors to accurately assess the extent of the cancerous area, determine the boundaries of the lesion, and monitor its progression.

Region Splitting and Merging Technique

In Region splitting, the entire picture is first taken as a solitary district. In the event that the locale doesn't observe the predefined guidelines, then it is additionally partitioned into various districts (normally 4 quadrants) and afterward the predefined rules are completed on those areas to choose whether to additionally partition or to group that as a district. The accompanying system go on till there could be no further division of locales required i.e each district keeps the predefined guidelines. In Locale combining strategy, we think about each pixel as a singular area. We select a district as the seed locale to check in the event that nearby areas are comparable in light of predefined rules. On the off chance that they are comparable, we blend them into a solitary district and push forward to construct the fragmented locales of the entire picture. Both locale parting and district blending are iterative cycles. Generally, first locale parting is finished on a picture to part a picture into most extreme districts, and afterward these districts are converged to shape a decent fragmented picture of the first picture.

In the event of Region splitting, the accompanying condition can be really looked at to choose whether to partition a district or not. On the off chance that the outright worth of the distinction of the most extreme and least pixel forces in a locale is not exactly or equivalent to an edge esteem concluded by the client, then the district doesn't need further parting.

$$|Z_{max} - Z_{min}| <= threshold$$

$$Z_{max} = \text{Maximum Pixel Intensity value}$$

$$Z_{min} = \text{Minimum Pixel Intensity value}$$

c.) Fast CNN or deep CNN

A deep CNN version is created and used to do programmed plant species characterization with almost no customer connection. A CNN version may be created from a extensive variety of types of layers, for example, convolutional layers, pooling layers, absolutely related layers, and so on. These layers upload to creating herbal thoughts a reality. Convolutional layers are the facilities of a CNN version and incorporate of a gaggle of learnable channels. Albeit every channel isn't always spatially huge, they count on the a part of stretching out thru the overall profundity of the information records. In this manner, it's far feasible to perform the goal of getting a extent of neurons.

The proposed community accommodates of specific types of layers that are convolutional and absolutely related layers. The types of layers for CNNs. The type of the preliminary 5 layers is a convolutional layer, at the same time as the layer type of remaining 3 layers is a very related layer. A absolutely related layer has been used to interface present day neurons to each one of the neurons of the beyond layer. Generally, the engineering of the proposed profound gaining knowledge of business enterprise and the layers of the done community are made experience of withinside the subtleties that follow. Taking under consideration the end result of the convolutional layer demonstrates that preferred factors are surely the end result of this type of layers and a few manner or some other it thoroughly can be deciphered because the issue extraction process. The convolutional layer must be organized for extricating substantial examples from the information everyday snap shots in which the effects of the decrease layers, first and 2d convolutional layers, are just like the eliminated edges of the normal image and such closeness may be visible withinside the notion a part of the framework that's given in subsequent segment. By searching on the process of the absolutely related layer to the convolutional layer, the absolutely related layer behaves like a classifier withinside the traditional AI calculation. Regardless of the substantial process of the absolutely related layer, this sediment builds the intricacy of the version and it's far computationally steeply-priced undoubtedly.

The records (enter image) is 227×227×three and it's far separated with the aid of using a convolutional layer; it's far the primary convolutional layer of the profound business enterprise. This layer channels the information records with the aid of using usingninety six bits. The length of the portions is 11×11×three in which a step of four pixels has been chosen. The step is the space among the responsive subject groups of adjacent neurons in a bit map. In the occasion that the really well worth of the step became larger than the characterised esteem, the chance of dropping statistics could be expanded. In such case, the cross-over to the open fields could be faded and spatial components could be sooner or later faded. The type of the following layer is also a convolutional layer. Besides, standardization and pooling are likewise acted on this element. The first convolutional layer is trailed with the aid of using a response standardization layer as corrected direct unit (ReLU) neurons were used. One trait of those neurons is their unbounded actuations; hence, standardization is a essential level withinside the wake of using ReLU neurons. Then, at that factor, the community response standardization layer is trailed with the aid of using some other layer, referred to as pooling layer, and the type of this sediment is a most pooling layer. Its important responsibilities are to finish down-examining pastime and reduce the amount of obstacles prompting the diminishing of the computational expense. Thusly, it provides to forestalling overfitting because it offers a preoccupied form of the image portrayal. At the factor whilst the scale of the element is equal to three×three, it means that a district with this length can be pooled over. By using this type of layer, a cross-over can be available and substantial statistics approximately the region of article withinside the image might not be lost. The hundreds withinside the number one layer are instated from a Gaussian dispersion, in which its imply really well worth is 0 and its wellknown deviation esteem is 0.01. By exploring the really well worth of the same old deviation, placing greater modest really well worth effects in chocking enactments and making use of larger really well worth activates the blast of the actuation. In this sediment, neuron predisposition has been delivered with the aid of using using the constant 0. The end result of the number one layer is the contribution of the following layer.

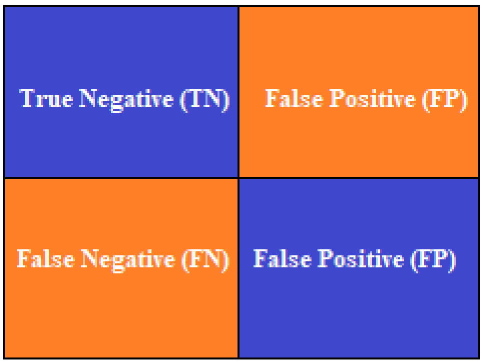
The ReLU activation function is:

$$y_i = \max(0;\ x_i)$$

Where x_i is the input of the ith channel. It is a fundamental functionality and quickens the union of stochastic inclination drop. Therefore, faster mastering will become workable because it gets rid of poor characteristics through using an exceedingly fundamental interplay with much less calculation value and maintains up with reminiscence usage proficiently. This functionality assumes on its legal responsibility properly certainly and provides to having the bottom and the pinnacle the identical at a comparable length. Consequently, its interest isn't always steeply-priced in evaluation with exceptional talents. Different talents, like sigmoid and exaggerated digression (tanh), cope with the problem of the perspective evaporating in which values create a long way from nothing. For instance, the slope of the sigmoid seems to be regularly extra modest because the outright really well worth increments. Then again, the ReLU functionality tackles the slope disappearing issue, and this functionality has one extra huge want over different capacity talents through thinking about the opposite perspective at the same time as considering computational expense.

Performance Metrics

The performance of the model is analyzed by using the confusion matrix. This will specify the performance of classification models for given test data. This will specify the values for test data that are known. This matrix is divided into two attributes such as predicted values and original values along with an overall number of predictions.



True Negative (TN): The prediction value is false and actual value is also false.

True Positive (TP): The prediction value is true and actual value is false.

False Positive (FP): The predicted value is true and actual value is false.

False Negative (FN): The predicted value is false and actual value is true.

Precision: This is specified that the total number of correct results obtained by the proposed model.

$$\text{Precision} = \frac{\text{TP}}{\text{TP} + \text{FP}}$$

F1 Measure: F1-measure is the metric that merges the recall and precision.

$$\text{F1 Measure} = 2 \times \frac{\text{precision} * \text{recall}}{\text{precision} + \text{recall}}$$

Accuracy: This parameter plays the major role in showing the overall accuracy.

$$\text{Accuracy} = \frac{\text{TP} + \text{TN}}{\text{TP} + \text{TN} + \text{FP} + \text{FN}}$$

Recall: This metric is mainly focused on reducing the false negatives.

$$\text{Recall} = \frac{\text{TP}}{\text{No. of TP} + \text{No. of FN}}$$

Table 1: Comparative performances for detecting Skin cancer and classification

Algorithms	Precision	F1-measure	Accuracy	Recall
GAN	85.67	86.89	87.12	84.91
Deep Convolutional GAN	89.34	89.56	90.23	91.12
Proposed Model	96.67	97.54	97.45	98.45

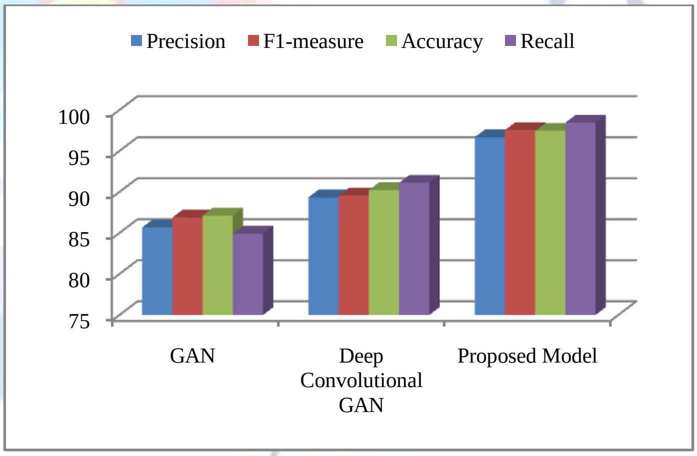


Figure 2; Comparative performances of various DL Algorithms

4. CONCLUSION

The detection of skin diseases using an ensemble machine learning approach has shown promise in improving accuracy and reliability in diagnosis. Ensemble machine learning methods, which combine multiple base models, have been effective in improving the accuracy of skin disease detection. These methods can capture different aspects of the data and reduce the risk of overfitting. Ensembles are often more robust to noise and variations in the data, which is crucial in skin disease detection where images may have different lighting conditions, angles, and other variations. By combining the predictions of multiple models, ensembles can reduce false positives and false negatives, making the diagnosis more reliable. The success of ensemble methods often relies on the diversity of the base models. Different algorithms, feature sets, or preprocessing techniques can be used to create diverse models. The quality and quantity of the data used for training the models are critical. High-quality, diverse datasets are essential for building effective skin disease detection models. Despite their improved performance, ensemble models can be more complex and less interpretable compared to single models. Ensuring that healthcare professionals can understand and trust the model's decisions is essential. Continual research and development are essential in this field. Future work can focus on increasing the speed and efficiency of skin disease detection models, as well as improving their ability to handle a wide range of skin conditions. Finally, the use of ensemble machine learning approaches for the detection of skin diseases is a promising area of research and has the potential to significantly improve diagnostic accuracy and reliability. However, it should be part of a broader healthcare system and involve collaboration between data scientists and medical professionals to ensure patient safety and accuracy in diagnosis.

Conflict of interest statement

Authors declare that they do not have any conflict of interest.

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