Journal of Nonlinear Analysis and Optimization : Theory of Applications Cost : 100-005 Component Editors-in-Chief : Sompone Ubiompongia Somyot Atlasteng

USING DEEP LEARNING ALGORITHMS TO SHOWCASE A NOVEL PROSPECTIVE METHOD FOR PRECISE SKIN DISEASE IDENTIFICATION AND CATEGORIZATION

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Abstract:

Skin cancer called melanoma can be lethal. When the development of melanocytes is out of control, it happens. The term "malignant melanoma" is one of several names for this cancer. Melanoma prevalence has never been higher, in both Australia and New Zealand. A melanoma diagnosis is predicted to occur in one in fifteen white New Zealanders at some time in their lives. The third most common kind of cancer in both men and women in 2012 was aggressive malignancy. While melanomas can develop at any age in adults, they are relatively uncommon in kids and teenagers. The uncontrolled proliferation of genetically modified melanocytic stem cells is thought to be the initial stage in the melanoma formation process. If melanoma is detected in dermoscopy photos at an earlier stage, the survival rate can be greatly improved. On the other hand, detecting melanomas is an extremely difficult task. Consequently, the detection and identification of skin cancer contribute significantly to the precision of pathologists. This study demonstrates a deep learning technique for accurately diagnosing the type of melanoma at an early stage. The proposed model differentiates between malignant lesions, superficial metastasis, and nodular melanoma. This enables the early detection of the virus and the rapid isolation and treatment required to control the spread of infection. The deep layer topologies of the convolutional neural network (CNN), which are neural network algorithms, are examples of deep learning (DL) and the conventional nonparametric machine learning method. Using information obtained from the website https://dermnetnz.org/, the efficacy of a CNN classifier was examined. The results of the studies demonstrate that the proposed method is more accurate in terms of diagnosis than the methodologies currently deemed to be state-of-the-art.

INTRODUCTION

Since the 1970s, skin cancer has been the most prevalent type of cancer in the globe. Over the past few decades, more people have been diagnosed with both nonmelanoma and melanoma skin cancer. According to the World Health Organization (WHO), one in three cancer cases is melanoma, and according to the Skin Cancer Foundation, one in five Americans will get skin cancer at some time in their life. Since hundreds of years ago, skin cancer has increased, particularly in the Western Hemisphere. Numerous other nations, including the US, Canada, and Australia, have also seen this tendency. Globally, infectious skin disorders have the potential to have a significant negative influence on people's health. Numerous studies, including one released in 2017 [1], demonstrate that skin cancer is responsible for 1.79 percent of the worldwide disease burden as measured in disability-adjusted life years. More than \$8 billion was lost by the Medicare programme in the United States in 2011 due to the high cost of treating skin cancer, which accounts for around 7

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percent of all newly diagnosed cancer cases globally [2]. Clinical evidence suggests racial disparities in the outcomes of skincancer: while people of colour are 20-30 times more likely to develop melanoma than whites, it has been found that people of colour either have a higher or lower mortality risk forspecific types of melanoma, depending on their skin tone. An accurate diagnosis of a skin condition is crucial for providing effective treatment. Using this technique, melanoma in dermoscopy photographs and images can be diagnosed at an earlier stage, increasing the likelihood of a successful prognosis. Dermatologists with extensive experience diagnosingthe many skin lesions that can be caused by melanomas are best suited to establish adefinitive diagnosis. Because there is no distinct boundary between skin lesions and the skin itself, because malignant and nonmelanoma skin lesions are visually identical, and because of other variables, diagnosing melanoma can be difficult. Pathologists would benefit immensely from the development of a reliable automatic detection approach for skin malignancies, such as a system that can automatically assess skin lesions. For our time, when information is so limited, this is of paramount importance. This research concluded that the accuracy and precision achieved by using the K-nearest Neighbors, Support Vector Machines, and Decision Trees classification methods was inadequate. Further investigation into the mathematical foundations of categorization revealed that using Deep Learning models was the most cutting-edge approach to achieving the desired results (also known as deep learning models). We tried a wide variety of mathematical models, with and without the aid of a learning algorithm. Our analysis led us to the conclusion that pre-trained models fell short in terms of the breadth and quality of activation they provided. Therefore, we pooledour mathematical knowledge to create a model called a Dense Convolutional Network, which achieved an accuracy of over 86.6%. By employing Deep Learning, a subfield of AI with outstanding strength and power, we were able to achieve efficient and trustworthy photo categorization. This artificial brain was very similar to the human brain in both structure and operation. Like the human brain, information was transferred, data was categorised, and conclusions were drawn and acted upon by firing neurons across the brain. Deep Learning is a type of machine learning that makes use of Neural Networks. In computer science, a NeuralNetwork structure is a multi-layered stack of interconnected components. Neural networks, astheir name implies, are able to carry out operations that are analogous to those that neurons in the brain are capable of carrying out, such as the recognition of patterns and the generation of predictions. The ultimate goal of the project is to develop a skin cancer screening technology that is both quick and easy to use by the general public. The sooner the condition is diagnosed, the greater the chance of a complete recovery. Most skin cancers are curable if detected early, as stated by the American Academy of Dermatology. There is still the matter of performing a skin biopsy after the trained model has been completed. If you want to know for sure if you have skin cancer or not, you should see a dermatologist and have a skin biopsyconducted. Simply said, this is the only way to receive a proper diagnosis.

RELATED WORK

Time is wasted when patients must go to dermatologists for a manual diagnosis of skin conditions. This is not a common choice in more remote locations. These residents of rural areas must visit a larger metropolis for medical care. There's a lot of manual labour involved here. Moreover, even a visit to the doctor can set you back a pretty penny. This includes interacting with other people, which is a necessary evil in this pandemic. Only a few number of diseases can be spread from person to person. To function within the current framework, physical interaction is required. In the current state of computer-aided diagnosis, burns and injuries are classified as skin illnesses. These approaches lack the required precision. Therefore, it is important to create a computer-assisted system that can automatically diagnose skin disorders and distinguish them from other skin issues. Color and texture features in images were employed by QuanGan et al. [3] to diagnose skin disorders. The pictures were preprocessed with a median filter. The image segments are obtained by rotating denoise images. Herpes, dermatitis, and psoriasis were classified using SVM after text features were extracted using the GLCM tool. A methodology for automatic eczema diagnosis and severity measurement based on image processing and a computational algorithm was proposed by MdNafiulAlam et al. [4]. By having patients upload a picture of their eczema, the system was able to both diagnose the condition and assess its severity. This method identified eczema and distinguished between mild and severe cases by the use of picture segmentation, feature extraction, and statistical classification. After classifying the eczema, a severity score was applied to the corresponding photo. In further studies, researchers included Deep Learning strategies for categorising skin disorders. In order to categorise skin illnesses, Parvathaneni Naga Srinivasu et al. [5] employed a deep learning framework based on MobileNet V2 and Long Short Term Memory. The spread of the disease was predicted using a co-occurrence matrix of grey levels. On the HAM10000 skin disease dataset, the algorithm has obtained an accuracy of 85%. S.Malliga et al. [6] trained and classified various clinical pictures using the CNN algorithm. They've chosen to suffer from three distinct skin conditions. Accuracy was 71% for these diagnoses: melanoma, nevus, and seborrheic keratosis. Using AlexNET, a pre-trained CNN model to extract the features, Nazia Hameed et al. [7] developed, implemented, and evaluated a system to categorise skin lesion images into one of five categories: healthy, acne, eczema, benign, or malignant melanoma. Classification accuracy using an SVM classifier was 86.21%.

METHODOLOGY

The foundation of artificial intelligence is self-learning algorithms. As soon as these algorithms obtain new knowledge about the task at hand, they continue to evolve [59]. They are continually enhancing their methods for resolving these issues. The term for this processis machine learning (ML) [12]. Self-learning algorithms are functional because they are basedon models that are roughly analogous to the human brain [3]. Similar to human nerve cells, artificial neural networks (ANNs) are comprised of nodes (neurons) that are connected at varying levels. Information is recorded, processed (by positive or negative weighting), and output as a result within this network of neurons. ANNs have a very large number of levels and can therefore recognise more complicated patterns, making them particularly promising. Deep learning refers to the learning processes that such networks are capable of [55, 58]. TensorFlow and Keras, two of the most prominent applications for image recognition, were utilised in the development of this paper's methodology.

DATA SET DESCRIPTION

The data comprises of 23 skin disease photographs obtained from http://www.dermnet.com/dermatology-pictures-skin-disease-images. The total number of photos is roughly 19,500, of which approximately 15,500 have been divided between the training set and the test set.

The photos are in JPEG format and have three channels, namely RGB. The resolutions vary from image to image and category to category, but typically, these are not exceptionally high-resolution photographs.

Acne, melanoma, eczema, seborrheic keratoses, tinea ringworm, bullous disease, poison ivy, psoriasis, vascular tumours, and so on are all examples of skin conditions. In this analysis, we used data on seven different types of skin illnesses, including molluscum contagiosum warts, systemic disease, seborrheic keratosis, nevus, bullous, actinic keratosis, acne, and rosacea. More than 7,000 dermatoscopic images can be found in this data set. New photos (750 in total) depicting burns and cuts to the skin have been added to the Dataset. Burns and cuts to the skin are considered skin disorders by current classification systems. Cut and burn injury pictures were gathered and contributed to the data collection to help with this issue. For the purpose of data analysis, a random (rand) function is used to divide the data set into two distinct sets: the training data (5900 records) and the validation data (1000 records) (1930).

PROPOSED FRAME WORK

The proposed system is a web application that serves as a first stage in the process of disease diagnosis by allowing a user to submit a photograph of the affected skin, at which point the user is informed as to the type of condition and provided a few recommendations. In order to identify skin conditions, the suggested system uses deep learning. The photographs will be analysed, processed, and categorised using computer methods based on a number of different characteristics of the images. Figure 1 depicts the architecture of a system for identifying and categorising skin diseases.



Figure 1 Proposed architecture diagram for SDDC-DL

DEEP NEURAL NETWORK ARCHITECTURES



Fig 2 CNN Architecture

CNN Architecture Figure 2 depicts the layers of a Convolutional neural network, from input to hidden to output. Levels in the middle of a feed-forward neural network are known as "hidden" because the activation function and the final convolution effectively obscure the information flowing into and out of those layers. Convolutional neural networks have hidden layers that actually execute convolutions. Typically, the Frobenius inner product is used, withthe ReLU activation function. The input of the subsequent layer is informed by a feature map generated by the convolution operation as the convolution kernel slides along the input matrix. Layers such as pooling, fully connected, and normalization come after this. The input is convolved by a convolutional layer, and the result is passed on to the following layer. By merging the results of multiple neurons in one layer into a single neuron in the next, "pooling layers" can reduce the number of data dimensions. [8] In fully connected layers, each neuron in one layer communicates with each neuron in every other layer.

PROPOSED ALGORITHM

Algorithm.1 proposed algorithm SDDC-DL

Algorithm: skin disease detection and classification using deep learning [SDDC-DL] Inputs: skin image dataset D, no. of epochs e, batch size b

Outputs: Detection results P and evaluation results R

- 1. Start
- 2. $(T, V) \leftarrow Pre Process(D)$
- 3. F1 = ApplyConv2D1Layer(T1)
- 4. F1 = MaxPooling2D1Layer(F)
- 5. F2 = ApplyConv2D2Layer(T1)
- 6. F2 = MaxPooling2D2Layer(F)
- 7. F3 = ApplyConv2D3Layer(T1)
- 8. F3 = MaxPooling2D3Layer(F)
- 9. Add Flatten Layer to convert 3D Array to 1D Array.
- 10. Add Dense Layers with activation function ReLU
- 11. Add Dropout layer
- 12. Add Dense Layers activation function ReLU
- 13. Add Output Layer with Activation function Softmax.
- 14. F Final Feautres (F1, F2, F3)
- 15. M = Train Model (F)
- 16. For each epoch e in n
- 17. For each batch b in m
- 18. Update M
- 19. End For
- 20. End For
- 21. M' = Fit Model(M)
- 22. P = Detect(M')
- 23. Print P
- 24. End For
- 25. End

The algorithm in question makes use of a dataset of skin images and several model layers, as detailed in the first algorithm described here. Different layers of the model are set up in a certain way to boost performance. The algorithm's iterative phase operates across multiple epochs, resulting in periodic model updates.

PERFORMANCE EVALUATION METRICS

In numerous ML-based issues, the confusion matrix is used to derive metrics for assessing performance. Numerous works, such as [2], [3], [7], and [10], examine the various applications of the confusion matrix. Both TP and TN are right forecasts, whereas FP and FN are wrong.



Figure 2: Confusion matrix model

As presented in Figure 3, different cases in the confusion matrix are used to arrive at the performance measures. The performance metrics are expressed in Eq. (4) to Eq. (7).

$Precision = \frac{TP}{TP + FP}$	(4)
$\operatorname{Recall} = \frac{TP}{TP + FN}$	(5)
F1-measure = $2 * \frac{(precision + recall)}{(precision + recall)}$	(6)
$Accuracy = \frac{TP+TN}{TP+TN+FP+FN} $ (7)	

2. RESULTS AND DISCUSSION

Experiment findings are shown here. The proposed method is observed in action and its efficacy is assessed through an empirical investigation of skin diseases. The suggested method's outcomes are compared to those of preexisting feature selection algorithms andtheir underlying prediction models. Predictions can be made using ML models like NB and SVM, or the CNN model. When compared to conventional approaches, the proposed algorithm performs admirably. Hyper tweaking the findings of the suggested method is expected to improve the performance of the skin disease detection framework. The classification score comparison between the implemented algorithm and the suggested approach is presented in table 1 below.

model	precision	recall	F1-score	accuracy
naïve <u>bayes</u>	70	69	59	80
SVM	71	71	65	88
CNN	90	90	90	90

 Table 1 Model performance table



Fig 3 Models performance comparison graph



Fig 4 training and validation accuracy and loss graphs with respect to no.ofepoches



Fig 4 Confusion matrix of proposed algorithm

http://doi.org/10.36893/JNAO.2022.V13I2.1856-1873

CONCLUSION

In this study, a Convolutional Neural Network (CNN) model for melanoma diagnosis was created, assembled, and put to the test. The suggested method's overall accuracy of 90% shows that each level of our two-stage learning platform will perform as well as promised. Other classification techniques besides NB and SVM can also do this. Convolutional neural networks (CNNs), on which the suggested method is based, are effective in classifying data into a variety of categories. Our CNN classifier features a modular and hierarchical structure that not only performs better at classifying melanoma accurately than state-of-the-art machine learning methods, but also significantly decreases the amount of computing work needed.. One of the disadvantages of the method is that it is only tested on a single dataset.

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