The Analysis of Skin Image Classifier by Neural Network Approach

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ABSTRACT

As the thermal burn cases were increasing, with up to third-degree burns resulting in death. The neural network method can improvise the diagnosis process on emergency patients. The purposes of this project were to classify, develop, and analyze the images related to the thermal burns classification. This project was started by collecting the various type of burnt skin images and sorting it into four (4) folders. The training phase proceeded via Artificial Neural Network (ANN) method in parallel with the software of the mathematical technique to be able to generate the output of each degree stage of burn. Once the digital stages are completed, another real image of the melasma area was used as a test image to generate the scan results. The neuron number obtained from training data were classified according to the characteristics of the skin and the result accuracy. Overall, ANN assists the user to classify the burn images with optimum epochs. It cannot be overfitting, but the validation and testing lines on performance curves should be closed with minimal error. Ironically, the artificial neural network has the compatibility to assist the medical authorities such as major burn services, reconstructive surgeons, dermatologists, and neurologists to better improvise in the medical field.

Keywords: *neural network; thermal burn; human skin; neural images; diagnoses.*

eISSN 2773-5494,

Received for review: 2021-07-21
Accepted for publication: 2021-11-13
Published: 2021-12-01

Introduction

Thermal burns are listed among the highest number of injury cases caused by various environmental factors in human life. The enthusiastic doctors at Cho Ray Hospital in Vietnam classify as burns that affect the epidermis, dermis, fat, and muscle layers of the skin [1]. Generally, skin is the largest organ in human body that covered almost 16% of total body's weight [2] [3] [4]. The entire human skin is interconnected to the nerve system. The purpose of this project is to make an analysis and development on the thermal burn diagnosis. The diagnosis of skin burns becomes challenging because of the complications that can arise when recognizing the degree of burns. The complications include the dermis thickness, the burnt size, and the number of skin layers affected. The burn team first performs first aid and management on the first line and refers the case to related departments such as dermatology or neurology for the next care.

The image classification process includes database processing that compares predefined patterns with detected objects to define them as appropriate categories. The neural network is a method of solving pattern recognition, prediction, optimization, associative memory, and control. The other network is a convolutional neural network that can perform image feature representation automatically but it also is able to learn many conventional hand-crafted feature techniques [5].

Methodology

The basic method of the project involves data selection, training, and analysis process. The data selection is divided into four (4) degree burns to identify the best input image during the training process. The degree of burn on human skin is indicated based on the skin layer damaged. For the lists, the second burn is only on the upper layer of the epidermis, the second degree indicates the burn on the whole epidermis layer, the third degree involves the whole dermis layer, while the fourth degree involves subcutaneous fat and loss of nerves. That is how the neural network plays the role. The ANN for this project uses the hidden layers' variation from the minimum, average, and the maximum; 10, 30, 50 layers. These layers determine the output accuracies instead of estimating the number of nodes.

Data Selection

Artificial network method (ANN) and convolutional network method (CNN) methods can identify the structure of burned skin [4]. The two neural network methods in Table 1 have been used to complete the analysis. The neural network must be programmed through MATLAB software.

Table 1: Idea selection

Options	**Neural Network Approach**	**Concept**
Idea 1	Artificial Network Approach (ANN)	A traditional method which is each neuron in every layer connected to every other neuron.
Idea 2	Convolutional Network Approach (CNN)	The sub-method of ANN and the last layer of CNN are fully connected.

Idea 1 is ranked as the best network method for any skin analysis because it can identify specific layers of the skin and the interconnected neural skin. Idea 1 from Table 1 is a traditional method to execute the skin layer which is still interconnected. Artificial neural networks (ANNs), or previously called neural networks (NNs), are computing systems inspired by the biological neural networks that constitute animal brains. The last decade has seen a revolution in deep learning, of which deep artificial neural networks (ANNs) are a key component. Artificial neural networks have been around and used in various applications since the 1940s [6]. Hence, ANN is the relevant method for upcoming skin analysis technology.

Idea 2 is still relevant for another neural network analysis. The advantage of using CNNs is their ability to develop an internal representation of a two-dimensional image [7]. Therefore, it allows the CNN model to recognize the position and scale-invariant structures in the data, which is one of the main data inputs while working on images.

Training Process

Approximately, large burnt skin images were obtained before arranging them respectively into the four classes in Figure 1. The cases and images were obtained based on the previous patient. The first step was to classify the images into four (4) burn degrees. Based on hundreds of skin images accepted, the number of images was simplified into 10 images for each class. Each image was loaded into its folder and graded into its respective levels using MATLAB software, respectively as shown in Figure 2. The input image has been placed in a monochrome version to support the infected area, including the approximate depth.

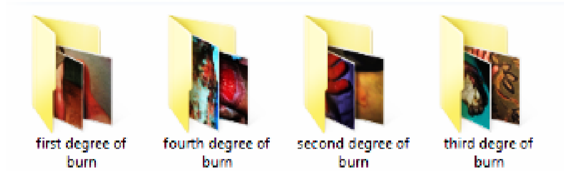


Figure 1: Classification of images by degree of burn.

Figure 2: Classify the input image as monochrome.

The image classification method in Figure 3 consists of converting the images into digital groups that will be used in the artificial neural network to train the network. Column 1 and column 2 represent the hidden layers in unit 'neuron'. In other terms, it was a step-up process before the output identified in column 3. At the end of the database setup, the group images were classified in column 3. After the database configuration was completed, the training and testing of the MATLAB coding in Figure 4 were performed to configure an actual image. The program is capable to recognize the images at their levels using the acquired and programmed database.

66x3 double

	1	2	3	4	5	6	7	8	9	10	11
1	0.2550	0.2204	1								
2	0.1541	0.1452	1								
3	0.8861	0.1282	1								
4	0.7646	0.1990	1								
5	0.9798	0.1131	1								
6	0.4942	0.0436	1								
7	0.9457	0.0882	1								
8	0.6063	0.1709	1								
9	0.8132	0.1839	1								
10	0.3176	0.0457	1								

Figure 3: Database set up.

```
clc;
clear all;
close all;
%% Taking an Image
[fname, path]=uigetfile('.jpg','Open an Image as input
for training');
fname=strcat(path, fname);
im=imread(fname);
im=im2bw(im);
imshow(im);
title('Input Image');
c=input('Enter the Class(Number from 1-12)');
%% Feature Extraction
F=FeatureStatistical(im);
try
    load db;
    F=[F c];
    db=[db; F];
    save db.mat db
catch
    db=[F c]; % 10 12 1
    save db.mat db
end
```

Figure 4: Image training and testing MATLAB coding.

Analyzing Process

An artificial neural network is made up of several layers, each with its neuron. Activation of one layer affects the next layer activation. In the next layer, the trigger model will generate a concrete model. Figure 5 describes the mechanism of an artificial neural network to perform the process of determining the most suitable network for analysis based on the number of hidden layers used. All of the images of the degrees of skin burn were trained by generating the table filters by using all of the data collected. Thus, the degrees of burn could be identified.

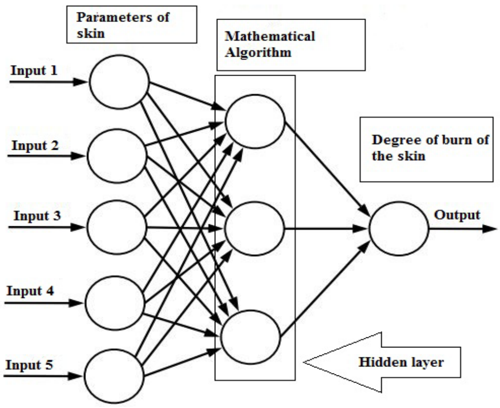


Figure 5: Neural network on degrees of burn recognition.

The neuron activation approaches another neuron to be close to each other. Therefore, the next layer must have a combination of subcomponents corresponding to the structure of the skin. Specifying a weight for each connector between the layers of neurons will facilitate the resulting configuration. Activating the first layer calculates the total weights against these masses. The sum of the weights of the pixels of the first layer was taken. Each neuron of the other layers must be connected to the neuron of the first layer to which its weight is associated.

Hidden classes operate by having an opinion bias. The size of the entry has been moved through the neural network. The input dimensions of the skin parameters are multiplied by the weight and added with the bias. The classification of the degree of the burn was determined by collecting data through the trigger function until the result of the extent of the skin burn is obtained. The output of the neural network was recognized around its real value structure point. All structural points were estimated by tablet stage according to Figure 6.

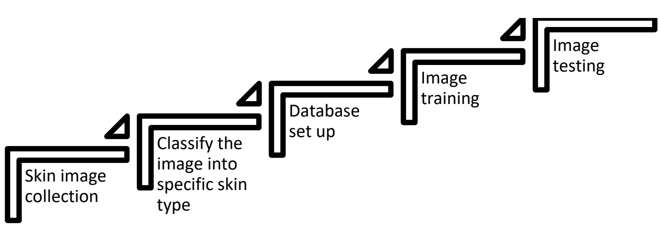


Figure 6: The basic working steps of ANN.

Results and Discussion

Data Collection

The number of hidden layers involved was 10, 30, and 50 layers. The hidden layers were allowed the users to model the complex data with assistance from their nodes. They were "hidden" because the actual values of their nodes were unknown in the training dataset. This method has been applied broadly for pattern recognition, sentence classification, speech and face recognition, text categorization, document analysis, scene, and handwritten digit recognition [8].

The hidden 10 class performance plot shows the square root mean square error. For data-driven training, validation, and testing, 10,000 failed. Based on the process using 10 hidden layers as a processing engine, it shows that the best validation for this process was 0.81377 in epoch 5. It was a higher validation error than other hidden layers applied to this activity. The best validation performance in 50 epochs was 0.43868. For the 50 hidden layers, the best line for learning is 1522 epochs and the best fit for the validation stream was 2 epochs. For the testing line, this shows that the line was adapted to 2 epochs. The validation performance value of 50 hidden layers was slightly lower than 30 hidden layers. The line is not compatible with this analysis.

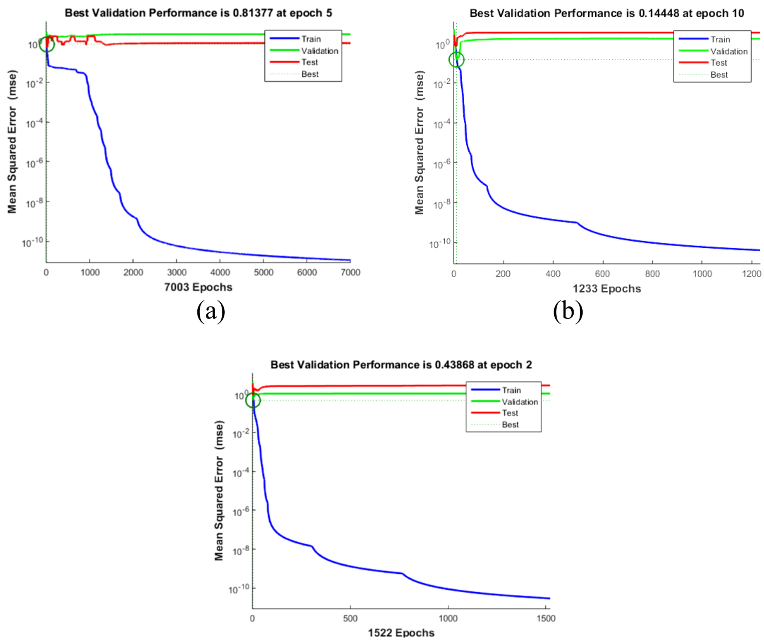
The activated neuron will approach another neuron to get closer. The analyzed appearance values are discussed for further analysis development in Table 2 as mean values. The mean of the training and test data was finalized from the raw data. In general, the training dataset is the broad term for samples used to build models, while the test dataset is used to determine the performance of the software. The data in Table 2 is expressed as a percentage.

Table 2: Average Skin Image Data

Class	**Average Data Points**	
	Training Data	Testing Data
1	0.5867	0.1268
2	0.5620	0.1204
3	0.3318	0.0936
4	0.2801	0.0975

Performance Plot

Based on Figure 7, the hidden layer's approach illustrated the optimal validation performance value was 0.14448 for 30 layers. Epoch refers to iteration number through the entire workout data set [9]. Each trace to be learned from the input data set is called an epoch [10]. Based on the executed data, the epoch of the value locator was 10 epochs. The larger the epoch numbers, the square error would be higher. Therefore, the ANN will identify the most stable epoch and maintain at one of the epochs such as Figure 7(b) on the green line.



(c)

Figure 7: Performance graph of neural network analysis for (a) 10 hidden layers, (b) 30 hidden layers and (c) 50 hidden layers.

By using 30 hidden layers, the best validation performance was successfully achieved. The program does not experience underfitting or overfitting to achieve the best validation performance. The trigger function can be applied by the input to produce the actual output. In addition, ANN can estimate hydrological parameters based on recorded measurements or observations [11].

The best validation performance for 50 epochs is 0.43868, while 10 hidden layers as their processing engine, shows that the best validation for this process is 0.81377 at epoch 5. Based on the testing curve on red at the earlier stage, the 10 hidden layers in Figure 7 (a) were not for the analysis. Their errors were detected validation process of using 50 hidden layers. The training data was undergone an overfitting situation and it was affected the error of the program. The error started to increase on the validation data set as the network start to overfit the data set of the training.

Regression Plot

Figure 8 reported the regression plot where the use of 30 hidden classes is reliable for the program [12]. The retracement line on the confirming pattern has fallen to nearly 45 degrees. The data output value is equal to the targeted data, as shown by the validator regression value which is 0.96887. The regression value for the training set is 0.91621. The value of the best-fitting line for the regression is 1 and it is acceptable. For the test set, the regression value is 0.65708. Therefore, the value is not reliable. The situation arose due to the lack of relevant information presented. The total regression response was 0.88833 which is acceptable for the analysis as the value is most frequently adopted.

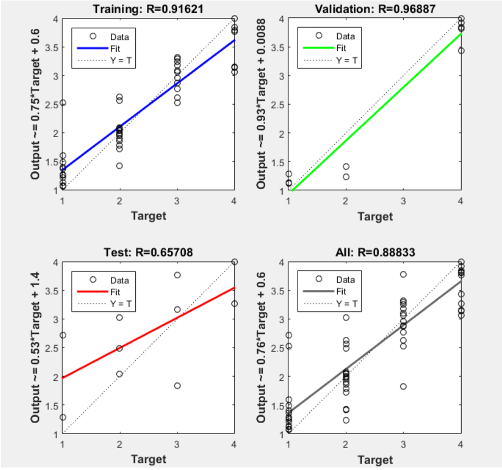


Figure 8: Regression plot on neural network training.

Training State Plot

In Figure 9, the value of the gradient coefficient for this approach that uses 30 hidden layers to do its calculation is 9.9866e8. The final values of the gradients reached their minimum when the epochs reach the value 1233. The gradient values and validation errors of this method appear to be as reliable as the network's learning. The value of validation errors for this approach is not high compared to other approaches. It shows that the validation checks for this approach are from 1223 to 1233 epochs. If the training instance is reliable, MATLAB will automatically stop training.

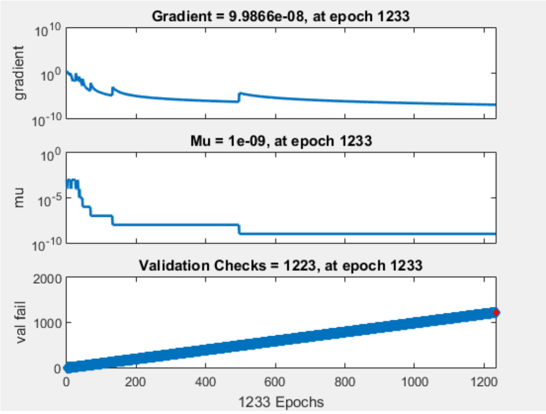


Figure 9: Training state plot on neural network training.

Conclusion

Overall, the nerve-related network engine program has taken over the experimental process to classify the class of every image that has been selected as the input of the program. This program also improves the desired feature of recognizing the image of burnt skin in a different types of sources although the skin has been infected [13]. From this study, it can be decided that the best number of the hidden layer that is needed as the computer-based performance to do the mathematical operation for this analysis is 30 hidden layers. The time taken for recognizing every image for each class is capable to reduce. For further improvement related to this project, a high-resolution image is necessary to be presented without background disturbance. It is preferable to capture the skin images on green cloth with a specific dimension. The more data selected as the input, the more reliable output will appear.

Acknowledgement

I want to extend my appreciation to the Ministry of Higher Education for the Fundamental Research Grant Scheme (FRGS) as referring to the grant number 600-IRMI/FRGS 5/3 (363/2019) as our official funding during my research.

References

[1] R. Jarusek, E. Volna, and M. Kotyrba, "Photomontage detection using steganography technique based on a neural network," *Neural Netw.*, vol. 116, pp. 150–165, 2019.

[2] M. W. Knight and N. J. Halas, "Nanoshells to nanoeggs to nanocups: optical properties of reduced symmetry core–shell nanoparticles beyond the quasistatic limit," *New J. Phys.*, vol. 10, no. 10, p. 105006, 2008.

[3] N. F. A. Manan *et al.*, "Determining hyperelastic parameters of human skin using 2D finite element modelling and simulation," in *2012 IEEE Symposium on Humanities, Science and Engineering Research*, 2012.

[4] L. Mahmud, N. F. Adull Manan, M. H. Ismail, and J. Mahmud, "Characterisation of soft tissues biomechanical properties using 3D Numerical Approach," in *2013 IEEE Business Engineering and Industrial Applications Colloquium (BEIAC)*, 2013.

[5] R. Chellappa *et al.*, "Guest editorial applications of artificial neural networks to image processing," *IEEE Trans. Image Process.*, vol. 7, no. 8, pp. 1093–1096, 1998.

[6] J. Berg and K. Nyström, "A unified deep artificial neural network approach to partial differential equations in complex geometries," *Neurocomputing*, vol. 317, pp. 28–41, 2018.

[7] J. Brownlee, "Machine Learning Mastery," 19 August 2019. [Online]. Available: https://machinelearningmastery.com/when-to-use-mlp-cnn-and-rnn-neural-networks/. [Accessed 12 November 2021].

[8] F. Siddique, S. Sakib, and M. A. B. Siddique, "Recognition of handwritten digit using convolutional neural network in python with tensorflow and comparison of performance for various hidden layers," in *2019 5th International Conference on Advances in Electrical Engineering (ICAEE)*, 2019.

[9] N. Mohd Nawi *et al.*, "An implementation of first and second order neural network classification on potential drug addict repetition," *EmAIT*, vol. 02, no. 01, 2021.

[10] J. Brownlee, "What is the Difference Between a Batch and an Epoch in a Neural Network?," *Machine Learning Mastery,* 2018.

[11] V. Gholami, M. J. Booij, E. Nikzad Tehrani, and M. A. Hadian, "Spatial soil erosion estimation using an artificial neural network (ANN) and field plot data," *Catena*, vol. 163, pp. 210–218, 2018.

[12] J. Jawad, A. H. Hawari, and S. Zaidi, "Modeling of forward osmosis process using artificial neural networks (ANN) to predict the permeate flux," *Desalination*, vol. 484, no. 114427, p. 114427, 2020.

[13] H. Baba, J.-I. Takahara, F. Yamashita, and M. Hashida, "Modeling and prediction of solvent effect on human skin permeability using support vector regression and random forest," *Pharm. Res.*, vol. 32, no. 11, pp. 3604–3617, 2015