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Skin Cancer Detection using CNN (VGG16) inculcated with CLAH and Gaussian Filter

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Abstract— Many techniques related to image analysis have been proposed by researchers which are being used to detect a large number of diseases. These images are carefully analyzed by radiologists and doctors, and after careful interpretation, the results are obtained which finally help in making an appropriate diagnosis. This is a complicated and time consuming task, which requires high levels of concentration. Therefore, the experts who analyze the images mustn't suffer from fatigue or other common problems that can impair their performance. The present study attempts to reveal how a deep learning model using CNN with VGG16 is effective for the diagnosis and detection of skin cancer at its early stages. Therefore under the scheme, the 4000 images of raw skin cancer tissues are evaluated. The diagnostic model starts with pre-processing of images using the CLAHE along with the inculcation of the Gaussian filter. Thereafter, using hyper-parameter optimizer stochastic gradient descent, along with the effective learning rate 0.001, incorporating the training epochs of 50 nos. and pertaining the batch size 32 is formed. Consequently, as a result, the accuracy achieved is 99.70%, with a loss value of 0.0055%, a precision of 99.75%, a recall of 99.75%, and an f1-score of 99.50% respectively.

Keywords- Cancer Detection, Deep Learning, Neural Network, Convolutional Neural Network, Contrast-Limited Adaptive Histogram Equalization, Gaussian Filter.

I. INTRODUCTION

Skin cancer is a disease origin by an alteration in the distinctiveness of the forming units i.e., cells that make up the skin from ordinary to malevolent, which causes these cells to separate hysterically and damage DNA [1]. The three most common types of skin cancer are categorized into three types, namely basal cell carcinoma, squamous cell carcinoma and malignant melanoma [2]. Every year approx. 5.4 million cases of cancer are diagnosed in United States and one in five Americans is diagnosed with a skin disease in their life span. Although melanoma represents less than 5% of all skin cancers in the United States, it is responsible for around 75% of all skin cancer deaths [3]. Several factors can trigger the onset of skin cancer, including genetic factors, increased UV radiation, infection, and others [6].

In the medical field, the investigation of skin cancer is generally conducted by a biopsy technique. That part of the skin tissue is taken to then be checked in detail whether the tissue is a cancer cell or not. However, this examining technique takes an extensive duration for a dermatologist and costs a lot of money [7]. While the estimated survival of skin cancer, if it is detected late, is only about 14%, it can increase by more than 99% if it is detected at an early stage [5]. Early detection and accurate diagnosis by utilizing images of the patient's cancer tissue which are then processed by a system with fast computing time are urgently needed to facilitate the populace recognize whether skin cancer is just an ordinary skin disorder, as well as assisting the medical field in reducing the risk of delays in treating skin cancer.

There have been several earlier types of research regarding the classification of skin cancer using CNN. Based on the study conducted by [5] testing by comparing algorithms and different dermatologist's seborrheic keratosis tumor versus keratinocyte carcinoma and benign nevus versus malignant melanoma. The author uses architecture CNN GoogleNetInceptionV3 that was pre-trained on around 1.28 million images from ImageNet's 2014 Large-Scale Visual Recognition Challenge. The study achieved an accuracy of 93.9%. Further research by [8] for swift and early recognition of skin cancer using K Nearest Neighbor classification is 86.67%. Meanwhile, the accuracy generated using CNN is 76.56%. Then the next research by [9] classified skin cancer into four classes using the CNN method with 3 hidden layers to obtain an accuracy of 99% with a loss of 0.0346.

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Referring to the problems and brief explanations of several research journals above, the method CNN proved to have good accuracy results though still there are gaps in improving accuracy results. In this study, it is desired to obtain maximum accuracy results with values loss lower than in previous studies. The number of images with four classification categories used, this study will use the CNN method with the VGG-16 architecture. Where the architecture of the VGG-16 model is the top-5 in the ILSVRC ImageNet challenge in 2014 which obtained an accuracy of 92.6% with a data set of more than 14 million images belonging to 1000 classes [10].

One of the sciences, which are constantly developing, is medicine, due to the great variety of different diseases that affect human health. These diseases can be as obvious as a common cold that can be treated at home without any complications; or, on the contrary, as other types of conditions that can go unnoticed until the symptoms begin to be obvious and that is when the lack of timely treatment can trigger disability, disability or even death of the patient. This is the most significant reason for the importance of an early diagnosis because there are silent diseases whose progress can be stopped or controlled if there is no possibility of curing them, all this with the help of rigorous controls to identify wounds, signs, symptoms, changes in the organism, etc [3]. Although these diseases can indeed be found in a first check-up by a health professional, it is also true that they can go unnoticed because their characteristics in the early stages are usually subtle and almost invisible, until their progress begins to be evident as it happens with diseases such as Alzheimer's, diabetes, cancer, among others.

II. PROBLEM STATEMENT

The skin is the most visible organ of the human body, so it is very sensitive to changes in its surroundings and can cause skin diseases, such as skin cancer. Each type of skin cancer has a different level of malignancy, so it requires an accurate diagnosis to be able to take the appropriate treatment. The shape, size and color of skin cancer sometimes look like other skin diseases and are often overlooked. Like Melanoma, this most malignant type of skin cancer has a very similar shape to a mole and requires precision to be able to tell the difference. Therefore, appropriate techniques are needed to system can classify skin cancer into 4 classes, namely, melanoma, squamous cell carcinoma, dermatofibroma, and nevus pigments and to improve the accuracy of skin cancer classification.

III. OBJECTIVE

This study aims to implement Deep Learning in the process of classifying skin cancer in system can classify skin cancer into 4 classes, namely, melanoma, squamous cell carcinoma, dermatofibroma, and nevus pigments, so that the classification results obtained have high accuracy.

IV. SIGNIFICANCE

1. Help to differentiate malignant and non-malignant skin cancer and to speed up diagnostic results using the scheme so that patients get treatment more quickly and accurately.
2. To help improve the accuracy of skin cancer diagnosis, especially for melanoma.
3. Make it easier for dermatologists to carry out the melanoma classification process.

V. RELATED WORK

The research [11] depicted that, almost any type of healthcare professional will use AI in the future and in particular Deep Learning. While the foundations of AI go back many years, from the first concepts put in value by A. Turing, W. McCulloch, and W. Pitts, it is not until now that Deep Learning has become popular and much accepted. A deep learning neural network is a model that allows detecting characteristics of a series of input data to end with a series of output data. Neural networks can perform various specific tasks, they can work with data such as text, audio, images, video, and numerical data. The results of the neural network will be predictions that must be compared with the objectives desired, in the health environment will be the diagnoses of the doctors, to determine the effectiveness of the operation.

The research [12] depicted that, the delay in early treatment is the main factor in the high mortality rate, late help is due to the patient coming to the medical unit after being in a high-stage condition. The medics diagnose tumors through the nerves of sight, hearing, and the level of reflection of the body. To find out the type of benign or malignant tumor, usually with a sampling process of cell tissue. Radiographic equipment Computer Tomography Scanner (CT scan) and MRI can be used to diagnose brain tumor detection.

The research [13] depicted that, the images generated from CT scanner radiology equipment. This large number of images will be used as training data by machine learning, aiming to obtain a matrix model (kernel). This model can then be useful in predicting new images whose labels are not yet known. The deep learning method used is CNN by choosing from many CNN architectures, namely the MobileNet architecture.

The research [14] depicted that, there are still many types of tumors that are not known because the location of the tumor is very difficult to reach. Types of brain tumors are divided into 2, namely glioma and non-glioma. Glioma is a type of tumor that grows from the supporting cells of the brain (glial), and non-glial cells grow outside of the support cells of the brain. Non-glial types are further subdivided into slow-growing tumors

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(meningiomas) and hormone-secreting tumors (pituitary). Subsequently, using the CNN approx. 96.90% of accuracy is achieved over Dataset-III and 95.75% of accuracy using Dataset-II.

The research [15] depicted that, GLCM is an scientific technique that generally can eradicate artifacts efficiently. In addition, it can also differentiate textures and images clearly. GLCM can determine pixel frequency, especially in an area different. Research on the validity and effectiveness of fuzzy-GLCM in the recognition of lung carcinoma by means of bronchoscopy images proves that the method shows 98% of accurateness.

The research [16] depicted that, after the image improvement process is carried out, and then image segmentation is carried out. Process segmentation makes it easier to further analyze and identify the information in the image. The thresholding method is the most effective image segmentation technique simple. This technique involves a threshold value that is used to change grayscale images into binary images.

Research [17] depicted that, the occurrence of skin cancer is considerably escalating each year due to the decline in the ozone layer in the environment that formulate additional ultraviolet radiation transient throughout. Skin cancer detection becomes extremely vigorous research ever since 2016 the ISIC has produced an outsized skin cancer picture dataset. Numerous types of investigation suggested hand-crafted image immoderation with machine learning, but the procedure is slightly complex. This research endeavors to examine the outcome of the image processing method, with contrast1augmentation by CLAHE and MSRCR as contrast augmentation with CNN. The output evaluation to MSRCR, CLAHE is further appropriate to be imposed on color1image augmentation for swift recognition of skin cancer vide CNN. However, the original and CLAHE-improved datasets furnish an accuracy of 91.89% in the training and an accuracy of 85.00% in validation. Whereas the MSRCT improved dataset furnish an accuracy of 92.18% in the training and an accuracy of 83.85% in validation respectively.

VI. PROPOSED MODEL AND RESULT

Based on the block diagram in Figure 1 the research will be divided into 4 stages. The first stage begins with an input image of skin cancer which then enters the stage of preprocessing. Stage pre-processing intend to develop image eminence so to facilitate it is expected to produce maximum output. This stage includes resizing imagery, CLAHE, and Gaussian Filter. After that, the image enters the model training stage using CNN with the VGG-16 architecture; so that it is obtained outputs of the best model for skin cancer classification. Then the system testing for classification and accuracy. Then the system testing phase consists of 4 test scenarios.

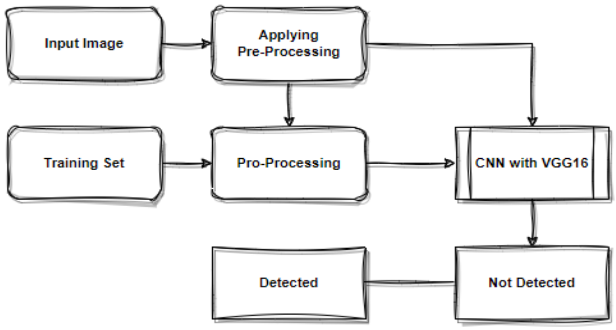

Figure 1. Block Diagram System

A dataset in this study was obtained from the open-access dermatologist's archive http://isic-archive.com i.e. International Skin Imaging Collaboration. The 4000 images are used, consisting of 1000 Melanoma images, 1000 Squamous Cell Carcinoma images, 1000 Dermatofibroma images, and 1000 Nevus Pigmentosus images in the format *.JPG. Dataset used is the image of cancer tissue. In the training and testing process, 75% of the training data and 25% of the test data are used. Figure 2 is an ex ample of skin cancer tissue image data obtained from ISIC.

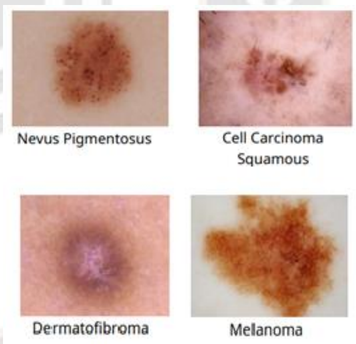

Figure 2. Skin Cancer Network Image Dataset

Stage pre-processing was performed as one of the scenarios to determine the best performance. Stage pre-processing includes several processes viz resizing imagery, CLAHE, and Gaussian filter. At the stage of resizing the image, the process of changing the size of the digital image from various sizes to a size of 64x64 pixels. On pre-processing CLAHE, there is an increase in the contrast value by giving a value clip limit (maximum value of the height of a classification of Skin Cancer using the method CNN with the VGG-16 Architecture histogram) so that the contrast can be increased but not excessive even though working in a local area [18]. Meanwhile, the Gaussian filter is a linear smoothing that selects the weights according to the shape of the Gaussian function, either in the spatial domain or in the frequency domain [19].

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The model training used in this study is CNN with the VGG-16 architectural model. CNN is the improvement of Multilayer Perceptron's planned to procedure two-dimensional data. Therefore, CNN is incorporated in the nature of Deep Neural Networks since the structure has high network intensity and is extensively used on image data [9]. The CNN method itself is generally divided into a feature extraction layer and a classification layer. On the feature extraction layer, inputs incoming image convolutional layers, layers RelU activation, and pooling layer. Next, on classification layer cover the fully connected layer and the activation layer softmax. Figure 3 shows the training architecture of the VGG-16 model.

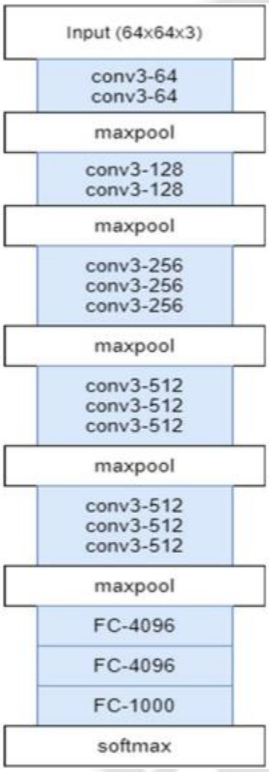

Figure 3. VGG16 Model Training

A confusion matrix is a technique used to calculate the performance of the process classification, which control information to facilitate balance of the classification results by the certain measures. There are four terms representing the results of the current classification performance measurement using the confusion matrix. Among them are Total True Negative (TTN), Total True Positive (TTP), Total False Negative (TFN) and Total False Positive (TFP). Where based on the values of TTP, TTN, TFP, and TFN the accuracy values can be obtained, precision, recall, and f1-score [20].

The loss function is an important part when doing model training. This function measures how well the model performs the task of calculating the loss from the model output and the desired target. If the model prediction is wrong, then the loss value will be high. If the model prediction is good enough, then the loss value will be close to the old value. Categorical cross-entropy is one of the loss functions used to classify multi-class data. In short, there is data on one of many possible categories, but the model must decide on one. Formally, it is designed to measure the difference between two probabilities [21].

The CNN model is trained in depth by updating all layers in the network iteratively and the optimizer plays a very significant role. The gradient descent model is a ordinary alternative for optimizing neural networks [22]. To reduce the intent utility, the considered parameters are restructured in the overturn course of the objective function gradient. The optimizers used in this learning were SGD, RMSprop, Adam, and Nadam

System testing is carried out to find out the best performance results and to analyze what parameters affect system performance. At this stage the system testing is divided into 2, namely image resizing testing and testing using CLAHE and Gaussian filter pre-processing. Where in each test a hyperparameter influence scenario is carried out which includes the optimizer, learning rate, epoch, and batch size scenarios.

Image resizing testing is carried out by changing the size of the image, aiming to find the appropriate image size to produce maximum accuracy results. The image sizes to be tested are 224×224, 128×128, and 64×64 pixels, with several other parameters that have been determined, namely the SGD optimizer, learning rate value of 0.001, epoch 50, and batch size 32. Table I demonstrates the results of the accuracy of the resizing test image.

TABLE I. IMAGE RESIZING TEST

Image Size	Accuracy
128x128	98.59%
64x64	100.00%
32x32	99.80%

The next scenario is testing with using CLAHE pre-processing and Gaussian filtering. In this test there are 4 hyperparameter testing scenarios, namely looking at the effect of using the optimizer, epoch, learning rate, and batch size. The results of the test scenario are shown in Table II below

TABLE II. TEST RESULTS WITH CLAHE AND GAUSSIAN FILTER PRE-PROCESSING

Scenario 1: Optimizer (Learning Rate:0.001, Batch Size:32, Epoch:15)		
Loss	**Accuracy**	**Optimizer**
SGD	95.20%	0.1294
RMSprop	79.20%	0.9475

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Nadam	92.00%	0.1966
Adam	92.40%	0.3434
Scenario 2: Learning Rate (Optimizer Stochastic Gradient Descent, Batch Size:32, Epoch:15)		
Learning Rate	**Loss**	**Accuracy**
0.0001	84.70%	0.3609
0.001	95.20%	0.1294
0.01	94.90%	0.192
0.1	87.70%	0.4599
Scenario 3: Epoch (Optimizer: Stochastic Gradient Descent, Learning Rate:0.001, Batch Size:32)		
Epochs	**Accuracy**	**Optimizer**
75	100.00%	9.27E+00
50	99.70%	0.0055
25	97.10%	0.0601
15	95.20%	0.1294
Scenario 4:Batch Size(Optimizer: Stochastic Gradient Descent, Learning Rate:0.001, Epoch:50)		
Batch Size	**Accuracy**	**Loss**
128	99.70%	0.0098
64	99.40%	0.0168
32	99.70%	0.0055
16	99.80%	0.012

In the epoch scenario, the test results show that the highest epoch accuracy is at epoch 75 with an accuracy value of 100% with a loss of 9.27E+00. However, the best result chosen for the epoch scenario is 50, because the model work is not too heavy but has shown an raise in accuracy with every epoch and the variation in accuracy involving training and validation data is not much different.

Whereas epoch 75 still shows the appearance of many spikes as shown in Figure 4. In the batch size scenario, the accuracy results show that the highest batch size is 16 with an accuracy value of 99.80% and a loss of 0.012. However, the batch size 16 accuracy graphs in Figure 5 show the emergence of many spikes, so the best batch size is batch size 32. So, in the testing stage CLAHE pre-processing and Gaussian filter using the best hyperparameter, namely Stochastic Gradient Descent Optimizer, epochs 50, batch size 32 and learning rate 0.001 the final result is an accuracy value of 99.70% and a loss of 0.0055.

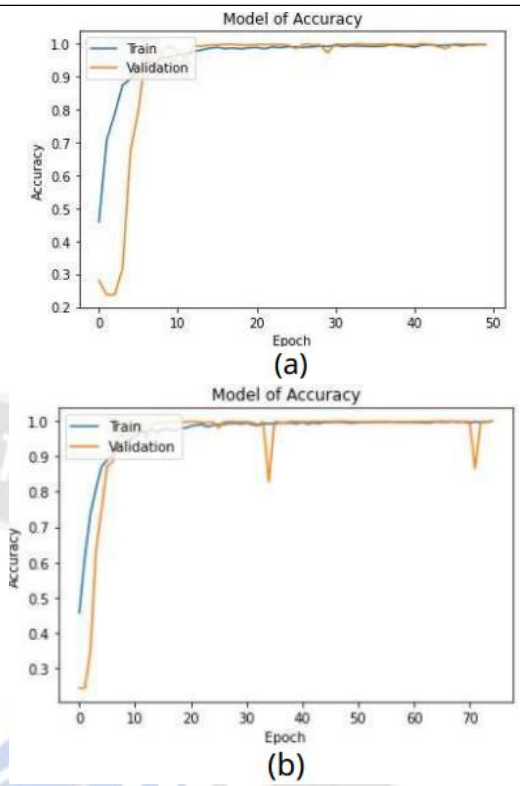

Figure 4. Graph of Testing AccuracyEpoch(a) 50 and (b) 75

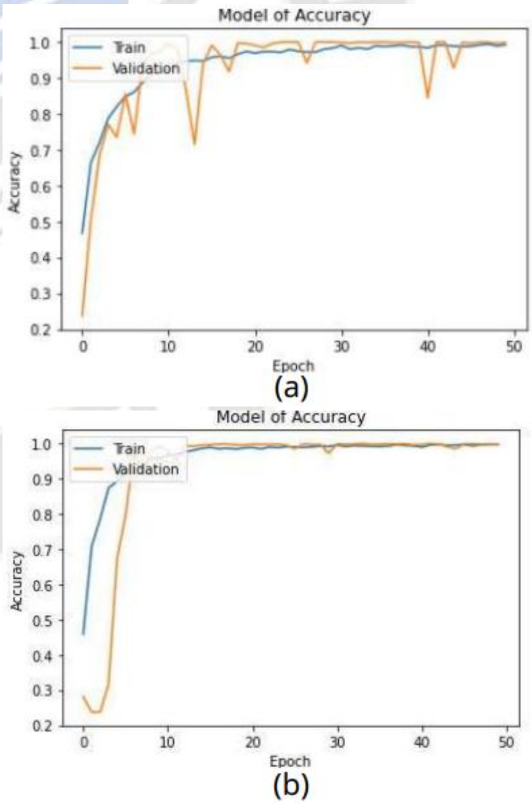

Figure 5. Graph of Testing AccuracyBatchSize(a) 16 and (b) 32

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Based on the outcome of the experiment scenarios shown in Table 2 the optimal results are in the test with pre-processing CLAHE and Gaussian filter. The results of the hyperparameter optimizer test scenario show that the SGD optimizer is considered the best in skin cancer classification using the CNN VGG-16 architecture method. The test results of the epoch hyperparameter scenario show that the greater number of epochs does not necessarily result in optimal performance. In this study, large epochs tend to show a sudden decrease at each particular epoch which results in spikes appearing on the accuracy chart. So in this study, the best epoch is 25 because the cost is low and the model work is not too heavy but has shown optimal results. For the results of testing the hyperparameter batch size scenario, the use of a smaller batch size has a faster convergence speed in the algorithm but produces noise in larger calculations, while the use of a larger batch size can help reduce noise but does not guarantee an increase in accuracy values. So that in this study, the batch size that produces the optimal value is batch size 32.

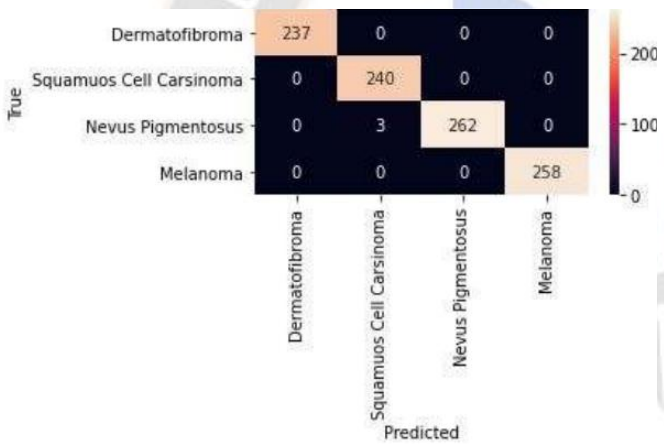

Figure 6. Confusion Matr

VII. CONCLUSION

Based on the test results, this study was able to design a system that can classify skin cancer using the CNN method with the VGG-16 architecture. The system can classify skin cancer into 4 classes, namely, melanoma, squamous cell carcinoma, dermatofibroma, and nevus pigments. In testing the system, test scenarios are carried out with and without pre-processing and scenarios for 4 hyperparameters, namely optimizer, learning rate, epoch, and batch size. Then the final results with the best performance and accuracy are obtained from the test results with CLAHE and Gaussian filter pre-processing. The image is resized to 64×64 pixels and optimizer stochastic gradient descent, along with the effective learning rate 0.001, inculcating with the training epochs of 50 nos. and pertaining the batch size 32. Consequently, as a result, the accuracy achieved is 99.70%, with a loss value of 0.0055%, a precision of 99.75%, a recall of 99.75%, and an f1-score of 99.50%. The increase in system accuracy values compared to previous studies shows that the VGG-16 architecture has precise and detailed capabilities in recognizing and classifying images. The system can be used as a tool for medical personnel to reduce the risk of delays in treating skin cancer.

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