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DeepSkin: Robust Skin Cancer Classification Using Convolutional Neural Network Algorithm

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Abstract
Classification of skin cancer is a growing research topic with significant challenges in image processing. Learning algorithms for classifying a kind of skin cancer have been presented in recent articles to accelerate the diagnosis process with a rapid and accurate diagnosis. However, effective detection of skin cancer requires extensive graphical data. Inspired by deep learning successful results in computer vision, A Convolutional Neural Network (CNN) is proposed in this study to build a skin cancer classification model. We conduct this experiment by collecting massive skin cancer datasets, conducting pre-processing, training models, and evaluating the performance. Based on the experiment result, the benign and malignant classification model can obtain a good accuracy with a slight loss. Therefore, the results obtained reached an accuracy of 54%.

Keywords:
Skin Cancer, Convolutional Neural Network, Classification, Deep Learning

1. Introduction

There is a growing phenomenon of people with skin cancer diagnosed in the current time. A lack of knowledge about early prevention of skin cancer of clinical knowledge cause getting worse of the disease. Several papers have developed various solutions with many datasets to construct effective skin cancer detection. However, it remains a shortcoming when extracting a large dataset to diagnose skin cancer [1].

Skin cancer ranks third after cervical cancer, uterine cancer, and breast cancer. Fortunately, if the doctor can detect rapidly, the condition may be treated and cured [2]. Conventionally, early treatment by a dermatologist against melanoma through biopsy method. The biopsy is the retrieval of skin tissue for laboratory examination that aims to detect the presence of a disease. However, the drawback of a biopsy is getting late results from the laboratory. Thus, a more sophisticated method is required to detect skin cancer with accurate results [3].

Another common technique is dermoscopy, which uses valuable imaging tools to detect skin diseases. However, It is challenging if the method lacks labeled and class-unbalanced datasets, so a new skin lesion classification technique is required [6]. Other related issues are visual resemblance between melanoma and non-melanoma lesions poor contrast between lesions and skin [7].

Some communities proposed an automated melanoma screening system to deal with the issues. It provides significant relief for a dermatologist to detect malignant skin lesions more quickly. As a result, the technique is more efficient with a higher classification performance than traditional processing approaches. However, the methods remain a drawback when hundreds of tagged photos are required per class for training, and this method can be a disadvantage [8].

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The improvement of computational technology for detecting skin lesions with multiple algorithms is greatly improved. But the overall verdict of the system based on clinical images and dermoscopy taken with conventional RGB cameras did not outperform the dermatologists. The data collection of sizeable hyperspectral skin lesions and high-quality images has flaws. Deep learning research is required to interpret better the rich information included in hyperspectral photos [9]. A study categorizes skin cancer by relying on biopsy procedures' training photos that aren't confirmed. The underlying problems that occur in this classification cause systematic errors, but their effect on the performance of classification tasks is unknown [11].

To detect melanoma cancer, a variety of computer-aided systems have been developed. However, designing a Computer-Aided Diagnosis system is quite challenging due to the nevus's problematic visual look. While the existing system still uses the traditional machine learning model [5]. In the skin classification problem, the conventional model utilizes machine learning such as SVM to a classification problem, is a reliable and precise model that overcomes various classification problems, especially melanoma classification. However, implementing the embedded SVM classifier is challenging due to the complex computations [4].

Current methods proposed the use of sophisticated learning techniques to classify skin cancers. Using of learning model can improve the sensitivity and specificity of the detection. Thousands of clinical photos were acquired to experiment with learning techniques, including benign and malignant illnesses. To produce a higher accuracy of the classification model, it requires training photos of the skin cancer dataset [10].

Several approaches presented deep learning algorithms to construct a classification model to identify dermatoscopy pictures. Furthermore, deep learning outperformed pathologists in identifying melanoma from histological images. However, the binary type in identifying melanoma does not reflect the reality of skin cancer screening in the clinic, where specific diagnoses must be re-examined [12].

A paper proposed CNN as skin malignancies classification in distinguishing melanoma and nevi. Several research use feature selection methods to choose the best mix of characteristics. However, due to varying degrees of visual disparity between lesion types and significant intra-class variations, automatic disease recognition with dermoscopy images is challenging. Those challenges cause the traditional learning algorithms to distinguish between melanoma and non-melanoma. The current paper suggests that CNN establish a skin cancer classification model for determining melanoma from nevi [13] to deal with the issues.

Therefore, this paper proposes a new skin cancer classification model by adopting a deep learning algorithm to detect cancer quickly and accurately. In the skin cancer classification research, our study has the following contribution:

1. We design a new classification model to study the classification of skin cancer. We build a model employing deep learning approaches rather than a traditional classification model to identify skin cancer. To prove the model, we get a high level of accuracy and a slight loss rate.
2. We evaluate the model for better and more efficient results on the classification of skin cancer. Then, we provide a metric assessment graph to prove the model's quality. This paper conducts the experiment using benign and malignant skin cancer datasets to produce a classification model. Using algorithms in deep learning, we can detect skin cancer accurately and efficiently.
3. Our study can produce an accurate and efficient skin cancer classification model using deep learning methods. Instead of conventional methods, the proposed model can differentiate between benign and malignant skin cancers.

Organization: The rest of this paper is prepared as follows: Part II provides insights into related work. Part III explains the problem definition of this study. Part IV describes the

experimental setup, including feature learning methodologies, datasets, and data pre-processing, while Part V gives the study's findings and extensive analysis. Finally, part VI summarizes the findings and identifies several unsolved issues in anomalous node research.

2. Related Works

Several papers have proposed various approaches to deal with the problem of skin cancer classification issues. A paper proposed an MLP NN method to detect melanoma. The results of 23 images with four training sets showed the lowest accuracy of 80% and the highest accuracy of 88.88% [14]. Another article utilized the MLP NN approach, an overall accuracy rate of 83.86 percent, with the lowest precision of 81.81 percent and the most incredible accuracy of 85.71 percent. [15]. A study discussed the process of pre-processing skin images and selecting features for melanoma diagnosis. The experiment result showed an accuracy of 0.835 and 0.845 [16]. Another paper proposed a region-based ROI method to classify melanoma with nevus cancer accuracy 97.9% and 97.4% [5]. Another article introduced the CAD method to differentiate melanoma from nevus lesions [23].

A paper employed K-mean and PSO methods to detect skin cancer with an accuracy value of 98.7% [23]. Furthermore, another article proposes K-Means Clustering to classify melanoma and non-melanoma. The system's suggested classification accuracy results are evaluated on five different classification types [24].

Another article focused on tiered SVM methods in FPGA for early detection of melanoma [4]. Another report using the MSVM method to distinguish the types of skin cancer with accuracy achieved about 96.25% [19]. Another paper used the FLIM method combined with machine learning. The findings demonstrate the effectiveness of combining FLIM with machine learning methods has excellent potential to develop effective computer-assisted diagnostic criteria for accurate detection of cancer in dermatology [10].

The current research explored CNN to classify melanoma in dermoscopy images [7]. A study proposed CNN methods to detect segmented skin lesions using the ISIC 2016, 2017, and 2018 datasets. In the article, accuracy improvement reached 0.78% of 81.60% and 81.57% [20]. Another study presented detection of other skin lesions using CNN with a novel regularizer. They achieved AUC-ROC up to 0.77, 0.93, 0.85, and 0.86, assisting medical practitioners in classifying skin lesions [21].

Another research proposed GAN-based data augmentation technology to categorize skin lesions in melanoma deoxy—balanced multiclass accuracy of 83.1 percent was reported. [6] The type of skin lesions in other studies also used style gun and dense net, producing good accuracy good reached [17]. Another paper proposed FCN-based DenseNet methods to classify skin lesions with 98% accuracy, a recall of 98.5%, and an AUC score of 99% [18].

Therefore, we propose a new model to address detecting benign and malignant skin cancers by introducing new learning techniques to train CNN models. We construct the model to detect benign and malignant skin cancer and help dermatologists diagnose skin cancer more quickly and accurately. Thus, it may be used as one of the primary sources for further research on skin cancer classification.

3. Proposed Method

The research employs CNN's algorithm to diagnose benign and malignant skin cancers utilizing datasets including a collection of soft and malignant skin cancer pictures. We proposed a model of skin cancer classification using CNN's algorithm. We adopt binary classification by dividing the data into two classes (normal and malignant). This paper

denotes the feature vector as *x*, with *a* bias *b*. This classification is done by passing the data into *a* function that has parameters. The position will be calculated as the weight of each feature on the vector by multiplying it by the parameters. Equation 1 can be rewritten as equation 2, where x_i is the *i-element* of vector *x*. This function has a range of [-∞,∞]. Table 1 describes the mathematical notation of the regularizer.

Table 1 Mathematical notation of the regularizer

Notation	Description
$\boldsymbol{x}$	feature vector
$\boldsymbol{b}$	bias
$\boldsymbol{w}$	Parameter matrix and vector
$\boldsymbol{x_i}$	the *i-element* of vector x
sgn	Output

$$f(\mathrm{x}) = \mathrm{x} \cdot \mathrm{w} + b \quad (1)$$

$$f(\mathrm{x}) = x_1 w_1 + x_1 w_2 + \cdots + x_N w_N + b \quad (2)$$

$$Output = \mathrm{sgn}(f(\mathrm{x})) \quad (3)$$

This regression function generates a constant value used for categorical class classification. We use thresholding or by providing a specific value limit. As such, if $f(x)$ >threshold, then it is entered into the first class and vice versa $f(x)$ < entry is entered into the second class. The threshold technique is applied by using the sign function (Equation 3) to change the value of the process to -1 and 1 as output (equation 4), where -1 represents the input categorized into the first class and the value 1 represents the input classified into the second class.

$$sgn(x) = \begin{Bmatrix} -1\ if\ x\ < 0 \\ 0\ if\ x = 0 \\ 1\ if\ x\ > 0 \end{Bmatrix} \quad (4)$$

In this paper, we investigate CNN as a sort of deep learning. CNN is also used to solve the challenge of analyzing and classifying digital picture data. Deep learning is a field of machine learning that can educate computers to perform human-like tasks. In the classification study, the optimizer, activation function, filter size, learning speed, and batch size all affect the accuracy of the CNN model [25]. On the other hand, CNN is a locally connected network [26]. CNN's algorithm has a convolution layer consisting of a set of filters that can be learned, often referred to as kernels [27].

The CNN's immersive design enables the extraction of a collection of distinct characteristics at multiple levels of abstraction without the need for operator intervention [28]. The CNN approach directly relates to the picture used to create the relationship mapping feature [29]. CNN's ability to automatically learn discriminant and invariant features from data [30].

Our model uses s CNN with a hidden layer for the training and testing model. In this case, the settings will be updated in the opposite direction as the gradient of the target function. The merging layer was employed in this research to improve and speed up training time. We also calculate the accuracy and drawbacks of training and testing [31].

Table 2 describes the mathematical notation of the regularizer. Here's the calculation of the model that we built as follows:

Table 2 Mathematical notation of the regularizer

Notation	Description
$\boldsymbol{x}\,(\boldsymbol{i})\ \in\ \boldsymbol{R}$	Input Features
$\boldsymbol{x}\,(\boldsymbol{i})\ \in\ \boldsymbol{Y}\ (\boldsymbol{e.g.R},\{\boldsymbol{0},\boldsymbol{1}\},\{\boldsymbol{1},\ldots,\boldsymbol{p}\})$	Outputs
$\boldsymbol{\theta}\ \in\ \mathbb{R}\boldsymbol{k}$	Model Parameters
$\boldsymbol{h\theta}\ ::\ \mathbb{R}\boldsymbol{n}\ \rightarrow\ \mathbb{R}$	Hypothetical function
$\boldsymbol{\ell}\ :\ \mathbb{R}\ \times\ \boldsymbol{Y}\ \rightarrow\ \mathbb{R}+:$	Loss Function

In this paper, we have used the formula given to compute optimization problems:

$$Minimize\ \Theta \sum_{i=1}^{m} \ell\left(h_{\Theta:}\left(x^{(i)}\right), y^{(i)}\right) \qquad (5)$$

This study made the hypothetical function $h\theta\ ::\ \mathbb{R}n\ \rightarrow\ \mathbb{R}$ in the processing of neural networks. Forward pass and backward pass will be computed in CNN to assess the gradient loss function in the model. The forward pass to convolve input matrix x_i with filter W_i to obtain convolution output $z_{i:}$ calculated as follows:

$$f\ :\ \mathbb{R}^n\ \rightarrow\ \mathbb{R}^m$$

$$z_{i:}\ (x_i) = w_i\ x_i + b \qquad (6)$$

w_i is a CNN filter, and b term of bias is a neural layer parameter during training. CNN uses several similar neurons between layers to execute extensive model computations with minimal parameters. The convolution layer's parameters are filters, and reverse propagation models are used to learn during training.

We shall calculate the vector value function in the backward pass $f\ :\ \mathbb{R}n\ \rightarrow\ \mathbb{R}m$ with Jacobian matrix $m\ x\ n$.

$$\left(\frac{\partial f(x)}{\partial x}\right) \epsilon\ \mathbb{R}^{m\times n} = \begin{bmatrix} \frac{\partial f_1(x)}{\partial x_1} & \frac{\partial f_1(x)}{\partial x_2} & \cdots & \frac{\partial f_1(x)}{\partial x_n} \\ \frac{\partial f2(x)}{\partial x_1} & \frac{\partial f_2(x)}{\partial x_2} & \cdots & \frac{\partial f_2(x)}{\partial x_n} \\ \vdots & \vdots & \ddots & \vdots \\ \frac{\partial f_m(x)}{\partial x_1} & \frac{\partial f_m(x)}{\partial x_2} & \cdots & \frac{\partial f_m(x)}{\partial x_n} \end{bmatrix} \qquad (7)$$

4. Experimental Setup

1. Main Idea

   This paper's primary purpose is to create a classification model to detect benign and malignant skin cancer using CNN's algorithm. Deep learning for medical image processing has recently advanced, allowing for the creation of more sophisticated diagnostics systems. Skin cancer diagnoses with learning techniques are novel approaches to produce great precision [32]. Based on the current research with a promising result in image analysis, we propose that CNN deal with massive skin

cancer classification data to produce better results than conventional learning approaches [33].

2. Dataset

To conduct this study, we gather skin cancer datasets from kaggle.com, consisting of benign and malignant skin cancer images. In this dataset, there is training and testing with 3297 images. Thus, this dataset consists of 80% training data with 2637 images and 20% testing data with 660 photos. Table 3 provides information about the datasets used in this study.

Table 3 number of datasets used

Dataset Label	OSN features	
	Training	Testing
Benign	1440	360
Malignant	1197	300

3. Data Preprocessing

In this study, we conduct pre-processing using a vectorization process where a process is required to transform previously unstructured data into structured data forms. The pre-processing method converts more than 3297 benign and malignant skin cancers images to produce a feature vector. Several stage processes are color placement, black frame removal, hair clip removal, wound area separation, feature normalization, and feature selection [34]. In addition, we use under sampling and oversampling for sampling techniques to make it easier for the CNN algorithm to accept image input [35].

4. Classification Method

This study builds a classification model of melanoma skin cancer (malignant) and non-melanoma (benign) with a training and testing process. We separate the dataset into two types of data at the training process: soft skin cancer and malignant skin cancer before pre-processing. The pre-processing step that we do is to simplify building a classification model using CNN.

In the testing phase of the process, we perform feature extraction. In feature extraction, 80% of vector training data and 20% of vector testing data are used in the network learning process or studying input data for the modeling process using the CNN algorithm. Then the network is tested on validation data. The valid model is then put to the test using vector testing data, which assesses the model's effectiveness in classifying benign and malignant skin cancers. Finally, after numerous stages, the CNN algorithm creates a classification model of benign and aggressive skin cancer.

5. Result & Analysis

This study gains accuracy by adjusting various hyperparameters to achieve the highest performance. For example, we alter epoch=50 and validation split=0.2 throughout the training and testing phase. Tables 4 and 5 show CNN's implementation, particularly training and testing.

Table 4 classification results with various optimizer functions

Hyperparameter	Optimizer	Training Accuracy	Testing Accuracy
Epoch = 50	Adam	0.7188	0.7128
Learning Rate = 0.0002	RMSprop	0.7750	0.7512
Validation Split = 0.2	SGD	0.6438	0.5312

Table 5 classification results with various optimizer functions

Hyperparameter	Optimizer	Training Loss	Testing Loss
Epoch = 50	Adam	0.6031	0.5103
Learn ing Rate = 0.0002	RMSprop	0.4538	0.5410
Validation Split = 0.2	SGD	0.6755	0.5312

The recall, precision, F1 score, and Confusion Matrix were used to assess the performance model (CF). First, this research article calculates memory to determine the percentage of benign and malignant skin cancer data sets. Next, precision determines the data set's level, which is identified as benign and malignant. Finally, we compute the precision-to-recall ratio to identify benign and malignant skin cancers with low precision if the test results are insignificant. As a result, we need an F1 score, the best combination of accuracy and acquisition.

Table 6 In benchmark datasets, recall, accuracy, and F1 scores.

	precision	recall	f1-score	support
False	0.55	0.42	0.47	261
True	0.54	0.66	0.59	266
accuracy			0.54	527
Marco avg	0.54	0. 54	0. 53	527
Weighted avg	0. 54	0. 54	0. 53	527

This paper also presents a Confusion Matrix that depicts the model's performance on the known test data. The confusion matrix, in particular, contains information on True Positive (TP), False Positive (FP), True Negative (TN), and False Negative (FN). This is helpful since the categorization results are often insufficiently represented in a single number.

Figure 1 shows the evaluation of the metric with the confusion matrix (CM) using the CNN algorithm. We can see the number predicted by our classifier from the confusion matrix, separately for the two classes. In the confusion matrix, the values obtained are TP = 175, TN = 109, FP = 152, and FN = 91.

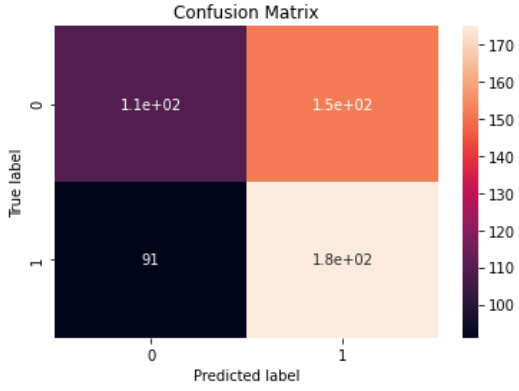

Fig. 1: Confusion Matrix

According to the confusion matrix results, the proposed model has a high TP score as positive data that is predicted correctly and TN as negative data that is expected rightly, indicating the maximum detection rate in distinguishing benign and malignant skin cancer. Notably, our approach delivers excellent accuracy and improves graph performance.

6. Conclusion

Skin cancer detection is a fundamental challenge for classifying benign and malignant cancers. To solve this challenge, the present way recommends using traditional machine learning. But it's expensive and time-consuming. Therefore, to enhance the classification model's performance, this research recommends using a CNN algorithm to develop a benign and malignant skin cancer classification model. We find that CNN achieves improved accuracy and reduced loss using the suggested model. As a result, the model might be a viable option for training the model on the hardware's remarkable computing capabilities.

Based on experiments, the proposed model can achieve high accuracy with little loss. get the maximum score = 0.538. Our approach produces higher accuracy and improves graphs performance based on the model performance. After training is completed, we obtain an accuracy score is 0.54, for the F1-score is 0.53, while the recall is 0.54 and the precision is 0.53. Our proposed model can produce higher accuracy and improve graphics performance. As a result, we suggest that a possible classification model is a potential approach for detecting both benign and malignant skin.

Further cancer classification research may benefit from the next model, which can be integrated with new approaches like the GAN algorithm in the future that could be combined with new techniques such as creating new regulators to train tissues.

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References

[1] Goyal, M., Knackstedt, T., Yan, S., & Hassanpour, S. "Artificial intelligence-based image classification for diagnosis of skin cancer: Challenges and opportunities." *Computers in Biology and Medicine*, 104065, 2020.

[2] 2. Pham, T. C., Doucet, A., Luong, C. M., Tran, C. T., & Hoang, V. D. "Improving Skin-Disease Classification Based on Customized Loss Function Combined With Balanced Mini-Batch Logic and Real-Time Image Augmentation.", *IEEE Access,* 8, 150725-150737, 2020.

[3] Wet, D. J., Steyn, M., Jordaan, H. F., Smith, R., Claasens, S., & Visser, W. I. ", An Analysis of Biopsies for Suspected Skin Cancer at a Tertiary Care Dermatology Clinic in the Western Cape Province of South Africa." *Journal of skin cancer,* Vol 2020, No 7, 2020.

[4] Afifi, S., GholamHosseini, H., & Sinha, R."A system on chip for melanoma detection using FPGA-based SVM classifier.", *Microprocessors and Microsystems,* 65, 57-68, 2019.

[5] Ashraf, R., Afzal, S., Rehman, A. U., Gul, S., Baber, J., Bakhtyar, M., ... & Maqsood, M. "Region-of-Interest Based Transfer Learning Assisted Framework for Skin Cancer Detection." *IEEE Access,* 8, 147858-147871, 2020.

[6] Qin, Z., Liu, Z., Zhu, P., & Xue, Y. "A GAN-based image synthesis method for skin lesion classification.", *Computer Methods and Programs in Biomedicine,* 195, 105568, 2020.

[7] Li, Y., & Shen, L. "Skin lesion analysis towards melanoma detection using deep learning network.", *Sensors,* Vol 18, No 2, pp 556, 2018.

[8] Harangi, B. "Skin lesion classification with ensembles of deep convolutional neural networks.", *Journal of biomedical informatics,* 86, 25-32, 2018,

[9] Johansen, T. H., Møllersen, K., Ortega, S., Fabelo, H., Garcia, A., Callico, G. M., & Godtliebsen, F. "Recent advances in hyperspectral imaging for melanoma detection.", *Wiley Interdisciplinary Reviews: Computational Statistics,* 12, 1, e1465, 2020.

[10] Fujisawa, Y., Otomo, Y., Ogata, Y., Nakamura, Y., Fujita, R., Ishitsuka, Y., ... & Fujimoto, M. "Deep-learning-based, computer-aided classifier developed with a small dataset of clinical

images surpasses board-certified dermatologists in skin tumour diagnosis.", *British Journal of Dermatology,* 180, 2, 373-381, 2019.

[11] Hekler, A., Kather, J. N., Krieghoff-Henning, E., Utikal, J. S., Meier, F., Gellrich, F. F., ... & Brinker, T. J. "Effects of label noise on deep learning-based skin cancer classification.", *Frontiers in Medicine,* 7, 177, 2020.

[12] Maron, R. C., Weichenthal, M., Utikal, J. S., Hekler, A., Berking, C., Hauschild, A., ... & Thiem, A "Systematic outperformance of 112 dermatologists in multiclass skin cancer image classification by convolutional neural networks.", *European Journal of Cancer,* 119, 57-65, 2019.

[13] Al-Masni, M. A., Kim, D. H., & Kim, T. S. "Multiple skin lesions diagnostics via integrated deep convolutional networks for segmentation and classification.", *Computer methods and programs in biomedicine,* 190, 105351, 2020.

[14] Sugiarti, Y., Na'am, J., Indra, D., & Santony, J. "An artificial neural network approach for detecting skin cancer.", *TELKOMNIKA Telecommunication Computing Electronics and Control,* Vol 17, No 2, pp 788-793, 2019.

[15] Wati, M., Puspitasari, N., Budiman, E., & Rahim, R. "First-order Feature Extraction Methods for Image Texture and Melanoma Skin Cancer Detection.", *Journal of Physics: Conference Series*, IOP Publishing, Vol 1230, No 1, 2019.

[16] Sari, Y. A., Hapsani, A. G., Adinugroho, S., Hakim, L., & Mutrofin, S. "Preprocessing of Skin Images and Feature Selection for Early Stage of Melanoma Detection using Color Feature Extraction.", *International Journal of Artificial Intelligence Research,* Vol 4, No 2, pp 95-106, 2020.

[17] Zhao, C., Shuai, R., Ma, L., Liu, W., Hu, D., & Wu, M. "Dermoscopy Image Classification Based on StyleGAN and DenseNet201.", *IEEE Access,* 9, 8659-8679, 2021.

[18] Adegun, A. A., & Viriri, S. "FCN-based DenseNet framework for automated detection and classification of skin lesions in dermoscopy images.", *IEEE Access,* 8, 150377-150396, 2020.

[19] Monika, M. K., Vignesh, N. A., Kumari, C. U., Kumar, M. N. V. S. S., & Lydia, E. L. "Skin cancer detection and classification using machine learning.", *Materials Today: Proceedings*, *33*, 4266-4270, 2020.

[20] Yang, Q., Qi, M., Wu, Z., Liu, L., Gao, P., & Qu, J."Classification of skin cancer based on fluorescence lifetime imaging and machine learning.", *Optics in Health Care and Biomedical Optics X*, International Society for Optics and Photonics, Vol 11553, 2020.

[21] Albahar, M. A. "Skin lesion classification using convolutional neural network with novel regularizer.", *IEEE Access,* 7, 38306-38313, 2019.

[22] Almaraz-Damian, J. A., Ponomaryov, V., Sadovnychiy, S., & Castillejos-Fernandez, H. "Melanoma and nevus skin lesion classification using handcraft and deep learning feature fusion via mutual information measures." *Entropy,* 22, 4, 484, 2020.

[23] Kaur, R., Gagandeep, Kumar, P., Babbar, G." An Enhanced and Automatic Skin Cancer Detection using K-Mean and PSO Technique", International Journal of Innovative Technology and Exploring Engineering (IJITEE), Vol 8, 2278-3075, 2019.

[24] Anas, M., Gupta, K., & Ahmad, S. "Skin cancer classification using K-means clustering.", *International Journal of Technical Research and Applications,* Vol 5, No 1, pp 62-65, 2017.

[25] Bhosle, K., & Musande, V. "Evaluation of deep learning CNN model for land use land cover classification and crop identification using hyperspectral remote sensing images.", *Journal of the Indian Society of Remote Sensing,* 47, 11, 1949-1958, 2019.

[26] Abdullah, A. A., Fonetta, A., Giong, D., Adilah, N., & Zahri, H. "Cervical cancer detection method using an improved cellular neural network (CNN) algorithm.", *Indones. J. Electr. Eng. Comput. Sci.,* 14, 1, 210-218, 2019.

[27] Manikonda, S. K., & Gaonkar, D. N. "IDM based on image classification with CNN.", *The Journal of Engineering,* 2019, 10, 7256-7262, 2019.

[28] Wang, Y., Peng, T., Duan, J., Zhu, C., Liu, J., Ye, J., & Jin, M. "Pathological Image Classification Based on Hard Example Guided CNN." *IEEE Access,* 8, 114249-114258, 2020.

[29] Chen, H., Miao, F., & Shen, X. "Hyperspectral remote sensing image classification with CNN based on quantum genetic-optimized sparse representation." *IEEE Access,* 8, 99900-99909, 2020.

[30] Shao, G., Chen, Y., & Wei, Y. "Deep Fusion for Radar Jamming Signal Classification Based on CNN." *IEEE Access,* 8, 117236-117244, 2020.

[31] Wanda, P., Hiswati, M. E., & Jie, H. J. "DeepOSN: Bringing deep learning as malicious detection scheme in online social network.", *IAES International Journal of Artificial Intelligence,* 9, 1, 146, 2020.

[32] Mohamed, E. H., & El-Behaidy, W. H. "Enhanced Skin Lesions Classification Using Deep Convolutional Networks." *2019 Ninth International Conference on Intelligent Computing and Information Systems (ICICIS)*. IEEE, 2019.

[33] Garg, S. Garg, H. Tripathi, V. Pant, B. Pant, K. "An Efficient Framework using Deep Learning for Skin Cancer Classification", rnational Journal of Innovative Technology and Exploring Engineering (IJITEE), 9, 2, 2278-3075, 2019.

[34] Swamy, R. S., Kumar, S. C., Latha, G. A." An Efficient Skin Cancer Prognosis Strategy Using Deep Learning Techniques.", Indian Journal of Computer Science and Engineering (IJCSE), Vol 12, No 1, 2021.

[35] Liebenlito, M., Irene, Y., & Hamid, A. "Classification of Tuberculosis and Pneumonia in Human Lung Based on Chest X-Ray Image using Convolutional Neural Network.", *InPrime: Indonesian Journal of Pure and Applied Mathematics,* 2, 1, 24-32, 2020.