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A combined approach of VGG 16 and LSTM transfer learning technique for skin melanoma classification

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***Abstract*---**To distinguish melanoma from other skin illnesses, doctors examine pigmented lesions on the skin. Damaged DNA causes cells to expand uncontrollably, and the rate of growth is currently increasing rapidly. Melanoma is a kind of skin cancer induced by UV radiation from the sun, with a survival rate of about 15-20 percent. Increased UV light on the earth's surface is also aiding the spread of skin cancer throughout the globe. Melanoma is diagnosed late, resulting in severe malignancy and spread to other bodily organs such as the liver, lungs, and brain. Melanoma diagnosis from dermoscopic skin samples automatically is a difficult problem. The purpose of Computer Vision, Machine Learning, and Deep Learning in the era of digital pictures is to extract information from them and develop new knowledge. Deep convolutional neural network (DCNN) models have been extensively studied for skin disease detection, with some achieving diagnostic results that are equivalent to or even better than dermatologists. Pre-processing involves first applying a filter or kernel to reduce noise and artefacts, then trained on a variety of tiny, unbalanced datasets to ensure that the moderately complicated models outperform the bigger models. Finally, to minimise overfitting, regularization DropOut is introduced. In this study, we present a transfer learned DCNN model for accurately classifying benign and malignant skin lesions using a deep learning technique. Our proposed DCNN model is combined VGG 16 and LSTM compared to other learning models to assess its performance using International Skin Imaging Collaboration datastores for this investigation (ISIC). We achieved the greatest training and testing accuracy of 90.89 percent and 94.39 percent respectively.

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***Keywords*---**Skin Melanoma, Transfer Learning, VGG 16, LSTM, Convolutional Layers, Maxpool.

Introduction

There are a number of deadly diseases in today's globe[1]. A family cancer is one of them. According to the World Cancer Research Fund, skin cancer ranks as the 19th most common cancer. According to the World Health Organization (WHO), skin cancer accounts for a third of all malignancies diagnosed globally excessive UV exposure produces DNA mutations in these cells, which promotes skin cell spread and eventually leads to skin cancer [2-3]. People in the United States, Canada, and Australia have been diagnosed at the greatest rates in recent decades. Skin cancer is caused by the uneven development of melanocytic skin cells. In the United States, 5.4 million new cases of skin cancer are detected each year. Melanomas account for fewer than 5% of all skin malignancies in the United States, yet they are responsible for more than 75% of all skin cancer-related mortality, with over 10,000 fatalities each year in the United States alone [4]. One out of every five Americans will be diagnosed with cutaneous cancer over their lifetime. In early age groups, females had much higher cancer rates than men, but significantly lower cancer rates in older age groups. Males and females differ the most between the ages of 20 and 24, with girls having a 2.5-fold greater age-specific incidence rate than boys. During skin lesion screening, dermatologists look at patient demographics, often known as patient data. To provide a more accurate clinical diagnosis, experts analyse characteristics such as the patient's age, anatomical region, cancer history, and skin phototype, among many others. If left untreated, this tumour has the potential to spread to other internal tissues and organs, rendering it lethal. People undergo expensive and time-consuming treatments to cure skin cancer, yet the death rate stays unchanged. Skin cancer is quickly becoming a severe ailment, and doctors are eager to identify it [5].

Many precancerous skin growths have symptoms that can be identified [6-7]. The most lethal skin tumours are both malignant and benign. Melanoma, carcinoma, sarcoma, squamous cell carcinoma, and skin lymphoma are all instances of malignant skin growths. In many cases, complete excision (surgical removal) leads to health. A benign tumour, on the other hand, has the ability to grow but not spread. Examples of benign skin growths include seborrheic keratoses, cherry angiomas, dermatofibromas, skin tags (acrochordon), pyrogenic granulomas, and cysts (epidermal inclusions).

A malignant tumour is a cancerous tumour that develops and spreads throughout a patient's body. Early identification of skin cancer can help to reduce mortality rates [8]. Deep Learning models offered the solution. They have the ability to infect other tissues and organs, as well as develop and spread uncontrollably. A precursor is a group of aberrant cells that have the potential to develop into cancer. Recognizing the frequent signs and symptoms of potentially malignant skin growths, as well as seeking medical attention when skin growths look suspicious, is critical when it comes to benign skin growths Manual diagnosis, on the other hand, involves the services of a dermatologist, and even then, diagnostic selection is subject to subjective variance in observation,

decreasing the patient's life expectancy [9]. As a result, an accurate automated melanoma detection system is crucial in supporting dermatologists in making accurate diagnosis decisions and minimising the amount of unnecessary biopsies. The dermatologist employs visual analysis to detect clinical signs of melanoma lesions such as asymmetry, irregular borders, colour change, diameter greater than 6mm, and mole evolution in order to make a diagnosis [10]. The American Cancer Society's ABCDE rule defines these melanoma symptoms. Dermatologists scan skin lesions, analyse clinical information from patients, and utilise their skills to classify lesions in order to detect skin cancer. Previously, skin cancer was found manually, which was time-consuming and costly. The fundamental purpose of melanoma detection is to identify pigmented skin lesions as benign or malignantv[11]. The first stage in doing this classification is to collect photographs of pigmented skin lesions in order to train the classification model with relevant labels. It is hard to overstate the importance of detecting and treating cancer in its early stages of development.

Dermoscopy images are collected with specialised equipment, whereas histological images are obtained by invasive biopsies and a microscope; both approaches yield highly uniform images [11-12]. Early identification is critical since the estimated 5-year survival rate for melanoma drops from over 99 percent if detected early to around 14 percent if detected late. However, the manual diagnostic accuracy of the ABCDE rule is 59-88 percent, and the precise diagnosis decision still requires a biopsy test for confirmation. Melanoma should be discovered precisely at this stage since it is curable. Early-stage melanoma can be treated by removing the melanoma-affected lesion.

The technique for categorising the data, on the other hand, is rather expensive. Accurate diagnosis, on the other hand, is difficult and requires sufficient training and expertise in dermoscopy, a non-invasive diagnostic procedure that employs optic magnification to allow visualisation of morphologic traits that are not visible to the human eye [13]. Unlike many other studies, label noise is not generated intentionally by random noise processes, but rather by real-world labels from (a) a large number of dermatologists or (b) a biopsy's histological diagnosis. Despite the fact that dermoscopic images improve visual clarity, precise melanoma diagnosis is challenging due to wide differences in colour, appearance, and shape, as well as the presence of artefacts such as hair, gel bubbles, and clinical rule marks.

Because the distribution ratio of lesion pictures in different skin lesion datasets may vary, a large quantity of labelled data is required to train the classification models and maintain adequate classification performance. Dermoscopy imaging methods are utilised to examine the skin lesion at a deeper level, which aids in melanoma diagnosis [14]. In dermatology, for example, ocular evaluation of a skin lesion reveals a substantial mistake rate when compared to gold standard pathology. Most current work in digital skin diagnostics prioritises a biopsy-verified test set since it has a reduced statistical error rate.

However, advances in deep learning in medical research have made it much easier [15]. Many academics have utilised CNN architectures to analyse skin cancer datasets in attempt to find a better technique to detect skin cancer early on. CNN architectures have been utilised by researchers in a number of

approaches to detect skin cancer. Deep Learning, namely the Convolution Neural Network, might be used to quickly and cheaply identify skin cancer using image categorization. CNNs are also widely utilised in object detection, face recognition, and other applications. CNN learns to generate spatial information hierarchies by using backpropagation and a variety of significant characteristics such as pooling (max/average) layers, convolution layers, and fully connected layers [16]. Several previous techniques needed extensive preprocessing, lesion segmentation, and extraction of domain-specific visual features prior to classification. This research project will benefit both medical science and deep learning professionals

Literature work

The authors [17] were focused the common problem of imbalanced dataset. They have created a simple DCNN model, with regulation control. The error calculated by combined mechanism of multi-weighted new loss and an end-to-end cumulative learning strategy. This work got high classification with low cost of computational. In the paper [18], focused on sequential images (with historical data) and used different convolution neural networks like Single image CNN, CNN-Score-Fusion and CNN-Feature-Pooling , CNN-LSTM and try to predict before going final stages. IVG to resemble its spatial characteristics performance metrics, this work not only classified optimal solution get by hyperparameter tuning. This method extract salient features from the dermoscopic images.

The next work [19], proposed a new CNN based metadata processing block for helping by enhancing the most related features. EfficientNet-B4, DenseNet-121, MobileNet-V2, and ResNet-50 these for CNN models are used. Change of parameter values and the accuracy, for that issue authors [20] done research on transfer learning, created a flexible architecture for handle changes in the training dataset in cloud, fog and edge computing. Distributed approach deals with reducing the running time. Normal skin and cancerous skin [21] with artifacts can mislead the model. The first procedure, morphological operations, cancerous region detection. In this work, Yolov4 used for the melanoma localization and segmentation for the better result.

The work [22], shows the review of various methods & algorithms used for skin melanoma classification. Selected 55 authentic work out of 5112 researches. The study discussed about pre trained models, handcrafted models, fully connected network models. The work covers almost all the datasets are available on the internet. Addressed one of the challenging factors like light reflections from the surface, various colour illuminations, different shape and size of the lesions [23]. First apply filter for remove noise and artifacts of the lesions. Next step is normalizing the images and extract the features from the data augmentation. The popular CNN models are used like AlexNet, ResNet, VGG 16, DenseNet and MobileNet.

The next problem focused on light weight and less complex DCNN [24] and the model is called LCNet Model. This work used some of well-known techniques like image resizing, over sampling and augmentation. The model use input image size 128×128×3, because of that achieved high processing speed. Developed a software tool in which a non-technical background person can develop complex deep

learning model [25]. Reviews different deep learning techniques [26] for early prediction. The various CNN based, KNN based, GAN with various datasets. Comparative analysis of 6 different TL algorithms [27] for multi class skin classification. The models VGG16, Inception v3, MobileNets, ResNet, etc. An app based for early stage [28], CNN base model trained 129450 images. The result certified by 12 board of certified dermatologists. CNN based model [29] with 804 of melanoma diagnosed by biopsy with 4 fold cross validation.

Introduced automated [30] CAD diagnosis system for multiclass skin melanoma with help of HAM1000 dataset. The work used 5 pretraining CNN models and ensemble models. The authors used [31] models like VGG16, support vector machine (SVM), RestNet 50 & some self-build models. The dataset used from Kaggle and all models compared with and got good result in VGG16. The work [32] deal with insufficient data and the work used Transfer Learning (TL) based SVM for features domain purpose. He used homogenous domain & heterogenous domain adaption. AdaBoost utilized to adjust the weight of wrongly classified data.

Proposed method

The public repositories of the ISIC include the greatest number of image lesions obtained via dermoscopic imaging. The collection is in JPEG or TFRecord format and comprises 30,500 photos at 1024 ×1024 resolution given by ISIC. The dataset is separated into two parts: the patient information and the patient skin photos, which might be melanoma or benign. There are six columns in the patients' details: image name, pid, psex, page, ploc, and target.

Data Preprocessing

To create a strong prediction model, data pre-processing techniques such as dealing with missing data, anomaly detection, duplicate and data imbalance over the dataset distribution class must be used. Using an assessment matrix, data augmentation is a strategy for increasing the learning of a proposed model by adding training data and assessing how much the training phase taught the model that is being evaluated. Other data augmentation methods include shift, flip, brightness, zoom, scaling, translation, add noise (salt & pepper), perspective transform, and others.

VGG 16 Model Configurations

VGG 16 developed Simonyan and Zisserman proposed by Visual Geometry Group, Oxford University. One of popular network VGG 16 is similar with LeNet and AlexNet. VGG 16 was Runner up of ILSVRC 2014, ImageNet is one of the challenging competitions happens every year, and all the researchers are come with new model for achieve maximum mechanism. CNN are the different categories in the sense no of convolution layer, no of maxpool and no of fully connected layers. VGG 16 is nothing but 16 different layers and these are the layer we can tuneable parameter. Other layers doesn’t contain tuneable parameter.

Table 1. Layers of VGG 16 Networks

Different Layers	No. of Layer
Convolution + ReLU	13
Maxpool Layers	5
Fully connected Network	3
Softmax layer	1

VGG 16 network accepts color images either melanoma or begin samples with size 224 * 224 (3 channels for color). Table 1 shows image passes through no of convolutional layer and all convolutional layer convolutional kernel size is 3 * 3 with stride 1 throughout all the layers. Its using row and column padding, size of input feature map and output feature map are same or the resolution of the feature map after convolution are same. The model contains 13 convolution layers, 5 max pool layers with window size is 2 with stride 2. Maxpool windows are non-overlapping windows. The advantages of the model are the network have a succession of nonlinearities because of that better discriminatory power in the network and largest receptive field on input is desirable. Not all the layers are convolutional layers and after maxpool layers, 3 fully connected dense layers. The first 2 fully connected layer 4096 channels. Here the hidden layer and other all layer used ReLU activation function. Figure 1 shows the detailed architecture diagram of VGG 16 netwok.

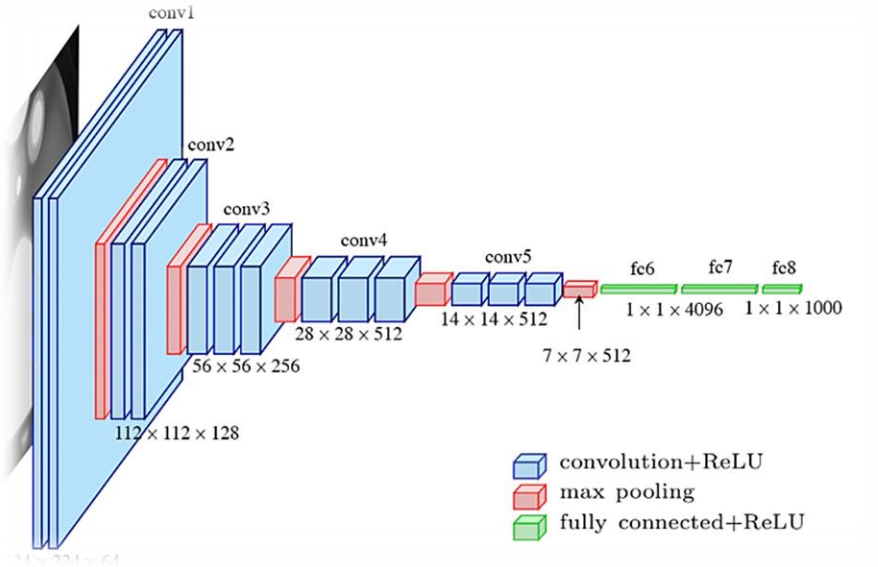

Figure 1. Architecture of VGG 16 Model

VGG 16 - LSTM Combined Feature Extraction

The characteristics obtained using max-pooling layers are typically passed to the fully connected layer for classification in VGG 16 networks. The suggested VGG 16 network, on the other hand, delivers the sequence of deep features to the LSTM layer rather than sending them straight to the fully connected layer for

classification. With great efficiency, the VGG 16 network extracts and recognises the image's local and global structures in the pixel series, whereas the LSTM network finds long-short-term associations.

The features extracted using max-pooling layers are often passed to the fully connected layer for classification in VGG 16 networks. However, in the proposed VGG 16 network, the sequence of deep features passes to the LSTM layer rather than directly passing them through the fully connected layer for classification. The VGG 16 network efficiently extracts and recognizes the image's local and global structures in the pixel series, while the LSTM network detects long-short-term dependencies. The suggested technique presents a combined VGG 16 -LSTM network for auto-identification and classification of skin melanoma in order to profit from the properties of the two models. There are two stages in the proposed VGG 16 -LSTM model. Convolution layers and max-pooling layers are part of phase one, whereas the LSTM layer is part of phase two. The convolution layers encode the local and global information of the fused feature set, while the LSTM layer decodes the encoded data. The data is flattened even further before being sent to a fully linked layer for categorization.

Transfer learning Mechanism

In the proposed Work, we used one of the methods is called Transfer Learning (TL). The depth of DNN number of parameters need to trained that increased tremendously, we can take pertaining network and fine tune it more advantages.TL is a operation use these trained parameters to other application. One dataset we can use it for training, and the learned parameters we can use with other application with different dataset. The features which are trained are domain dependent or general features. The first layer of CNN network learners' edges of the input of the training images like vertical, horizontal, diagonal, son on. Second layers learn about corners, compositions, etc, then features composition of second layers like eyes, face, nose etc. Continue further 4 th layer higher layers learns of abstraction, moving deeper layer the features are domain specific knowledge learns. Lower layers are more generic features- these lower layer knowledge we can transfer to some other application. Transfer learning and fine tuning together will give better performance on the application

Result and Discussion

In this section, discussion of the performance parameters like precision, recall and accuracy compared with existing models. The comparative results depend on the performance of our proposed model on the dataset and the calculation of true positive (TP), true negative (TN), false positive (FP) and false negative (FN) values.

Table 2. Precision Performance Comparison of combined VGG 16 and LSTM with Existing Models

Models	**Precision**
AlexNet	96.89
ResNet	84.94
VGG-16	88.27

DenseNet	91.00
MobileNet	84.62
combined VGG 16 and LSTM	95.62

The above table 2 represents, comparative results of precision values. Precision is the one of the parameter values is measuring that a model, proposition of positive identifications is actually correct.

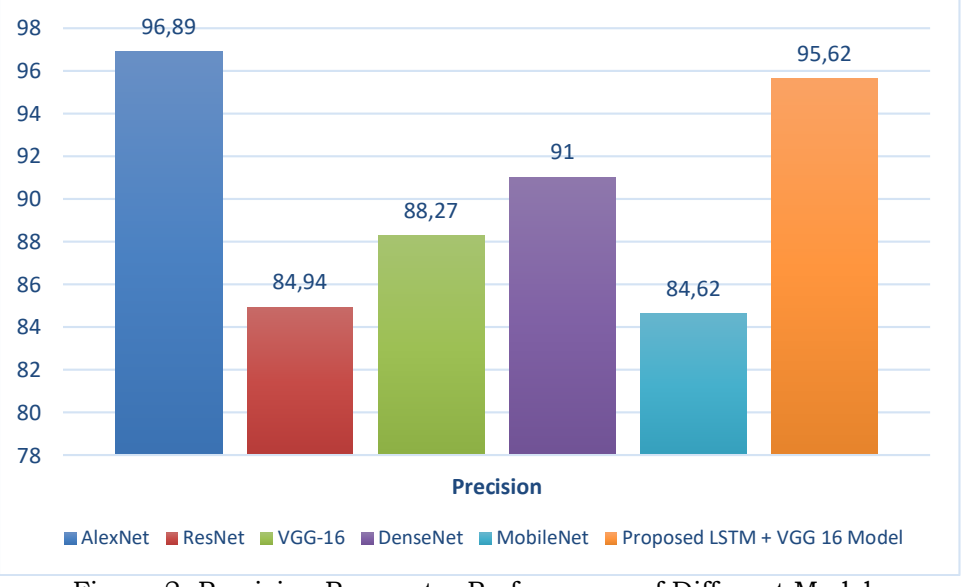

Figure 2. Precision Parameter Performance of Different Models

Precision value of different models are shown in figure 2. The precision of our proposed combined VGG 16 and LSTM model got good values compare with all the existing methods except AlexNet. The AlexNet and combined VGG 16 and LSTM difference in precision value is just 1.27 %. So, precision from the figure 1 conclude that proposed model is good.

Table 3. Recall Performance Comparison of Combined VGG 16 and LSTM with Existing Models

Models	**Recall**
AlexNet	90.70
ResNet	97.50
VGG-16	95.18
DenseNet	91.75
MobileNet	94.57
combined VGG 16 and LSTM	97.65

The above table 3, represents comparative results of recall values. Recall is the one of the parameter values is measuring that a model, proposition of actual positives is identified correct.

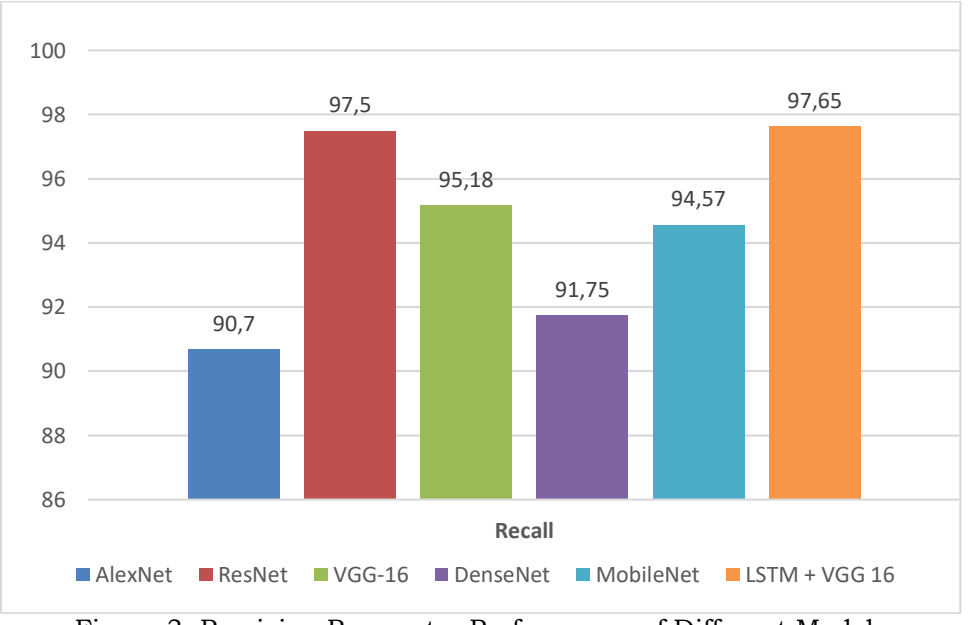

Figure 3. Precision Parameter Performance of Different Models

Recall value of different models are shown in figure 3. The precision of our proposed combined VGG 16 and LSTM model got good values compare with all the existing methods. So, recall from the figure conclude that proposed model is good.

Table 4. Training and Testing Accuracy Performance Comparison of Combined VGG 16 and LSTM with Existing Models.

Models	**Training Accuracy**	**Testing Accuracy**
AlexNet	92.05	88.81
ResNet	92.78	85.20
VGG 16	88.83	86.09
DenseNet	91.36	85.25
MobileNet	92.93	82.62
combined VGG 16 and LSTM	94.39	90.89

The above table 4 represents comparative results of training and testing accuracy values. Accuracy is the one of the parameter values is measuring that a model, fraction of the correct predictions of positive and negative sides.

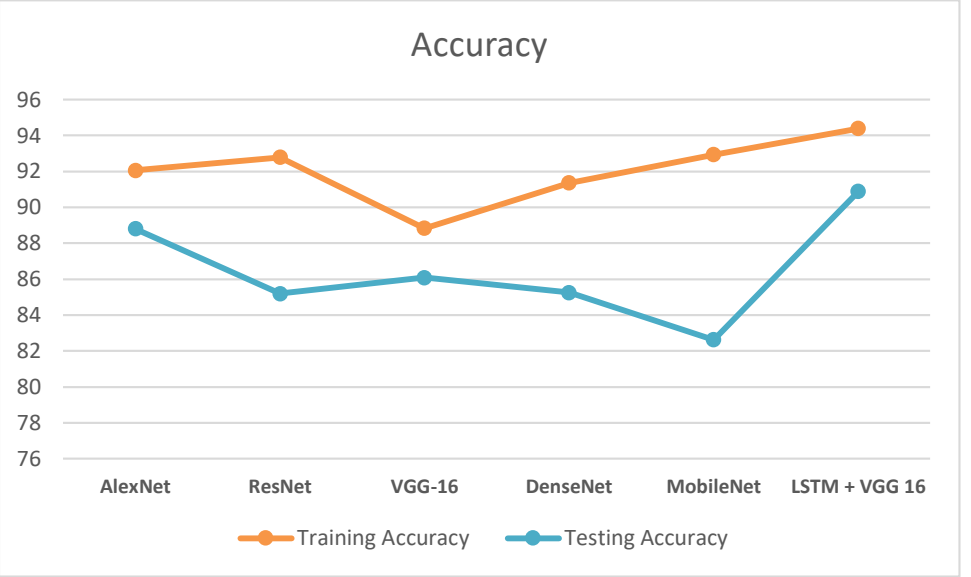

Figure 4. Training and Testing Accuracy Comparison of Different Models

Accuracy value of different models are shown in figure 4. The accuracy of our proposed combined VGG 16 and LSTM model got good values compare with all the existing methods. So, accuracy from the figure 3 conclude that proposed model is good. All the above models are totally free from overfitting and underfitting that we can understand when we compare each model training and testing accuracies.

Conclusion

The most prevalent kinds of skin cancer are benign and malignant varieties. Skin cancer is one of the most serious health issues that humans face. This illness is acquired when the pigments that give skin colour become cancerous. The symmetry, colour, size, form, and other characteristics of lesions are utilised to diagnose skin cancer and distinguish it from melanoma. Dermatologists face a difficult task in making a skin cancer diagnosis since many skin cancer colours seem same. As a result, early diagnosis of lesions is crucial and beneficial in totally curing skin cancer patients. Deep convolutional neural network (DCNN) models have been extensively studied for skin disease detection, with some achieving diagnostic results that are equivalent to or even better than dermatologists. Selection of various filters and their sizes, use of appropriate deep learning layers, network depth, and hyperparameter optimization are all important aspects of DCNN design. The limited size and data imbalance of publicly available skin lesion datasets, however, limit the use of DCNN in skin disease identification. This study includes information on a variety of CNN models as well as a comparison of their working procedures for determining the best outcomes.

Reference

1. S. Albahli, N. Nida, A. Irtaza, M. H. Yousaf and M. T. Mahmood, "Melanoma Lesion Detection and Segmentation Using YOLOv4-DarkNet and Active Contour," in *IEEE Access*, vol. 8, pp. 198403-198414, 2020, doi: 10.1109/ACCESS.2020.3035345.
2. Hosny, K.M., Kassem, M.A. & Foaud, M.M. Skin melanoma classification using ROI and data augmentation with deep convolutional neural networks. Multimed Tools Appl **79,** 24029–24055 (2020). https://doi.org/10.1007/s11042-020-09067-2
3. Q. Zhou, Y. Shi, Z. Xu, R. Qu and G. Xu, "Classifying Melanoma Skin Lesions Using Convolutional Spiking Neural Networks With Unsupervised STDP Learning Rule," in *IEEE Access*, vol. 8, pp. 101309-101319, 2020, doi: 10.1109/ACCESS.2020.2998098.
4. Pillay, V., Hirasen, D., Viriri, S., Gwetu, M. (2020). Melanoma Skin Cancer Classification Using Transfer Learning. In: Hernes, M., Wojtkiewicz, K., Szczerbicki, E. (eds) Advances in Computational Collective Intelligence. ICCCI 2020. Communications in Computer and Information Science, vol 1287. Springer, Cham. https://doi.org/10.1007/978-3-030-63119-2_24
5. J. R. Hagerty *et al.*, "Deep Learning and Handcrafted Method Fusion: Higher Diagnostic Accuracy for Melanoma Dermoscopy Images," in *IEEE Journal of Biomedical and Health Informatics*, vol. 23, no. 4, pp. 1385-1391, July 2019, doi: 10.1109/JBHI.2019.2891049.
6. Dorj, UO., Lee, KK., Choi, JY. et al. The skin cancer classification using deep convolutional neural network. Multimed Tools Appl **77,** 9909–9924 (2018). https://doi.org/10.1007/s11042-018-5714-1
7. Alphonse, A.S., Starvin, M.S. A novel and efficient approach for the classification of skin melanoma. J Ambient Intell Human Comput **12,** 10435–10459 (2021). https://doi.org/10.1007/s12652-020-02648-x
8. Filali, Y., Sabri, M.A., Aarab, A. (2020). Improving Skin Cancer Classification Based on Features Fusion and Selection. In: Bhateja, V., Satapathy, S., Satori, H. (eds) Embedded Systems and Artificial Intelligence. Advances in Intelligent Systems and Computing, vol 1076. Springer, Singapore. https://doi.org/10.1007/978-981-15-0947-6_36
9. Janney.J, B., Roslin, S. Classification of melanoma from Dermoscopic data using machine learning techniques. Multimed Tools Appl **79,** 3713–3728 (2020). https://doi.org/10.1007/s11042-018-6927-z
10. Esteva A, Kuprel B, Novoa RA, Ko J, Swetter SM, Blau HM, Thrun S.," Corrigendum: Dermatologist-level classification of skin cancer with deep neural networks.", Nature. 2017 Jun 28;546(7660):686. doi: 10.1038/nature22985.
11. Bhalla, S., Kaur, H., Dhall, A. et al. Prediction and Analysis of Skin Cancer Progression using Genomics Profiles of Patients. Sci Rep **9,** 15790 (2019). https://doi.org/10.1038/s41598-019-52134-4
12. Lakshminarayanan, A.R., Bhuvaneshwari, R., Bhuvaneshwari, S., Parthasarathy, S., Jeganathan, S., Sagayam, K.M. (2022). Skin Cancer Prediction Using Machine Learning Algorithms. In: Raje, R.R., Hussain, F., Kannan, R.J. (eds) Artificial Intelligence and Technologies. Lecture Notes in Electrical Engineering, vol 806. Springer, Singapore. https://doi.org/10.1007/978-981-16-6448-9_31

13. A. G. C. Pacheco and R. A. Krohling, “Recent advances in deep learning applied to skin cancer detection,” in Proceedings of the Neural Information Processing Systems (NeurIPS), Retrospectives Workshop, Vancouver, Canada, December 2019.
14. Singh, L., Janghel, R.R. and Sahu, S.P. (2021), "TrCSVM: a novel approach for the classification of melanoma skin cancer using transfer learning", Data Technologies and Applications, Vol. 55 No. 1, pp. 64-81. https://doi.org/10.1108/DTA-06-2020-0126
15. NIH National Cancer Institute, “Cancer facts and figures 2020,” CA: A Cancer Journal for Clinicians, vol. 70, pp. 1–76, 2020, https://www.cancer.org/cancer/bladder-cancer/detection-diagnosis-staging/survival-rates.html.
16. Yunendah Nur Fu’adah;NK Caecar Pratiwi;Muhammad Adnan Pramudito;Nur Ibrahim; (2020). Convolutional Neural Network (CNN) for Automatic Skin Cancer Classification System . IOP Conference Series: Materials Science and Engineering, (), –. doi:10.1088/1757-899x/982/1/012005
17. P. Yao *et al.*, "Single Model Deep Learning on Imbalanced Small Datasets for Skin Lesion Classification," in *IEEE Transactions on Medical Imaging*, vol. 41, no. 5, pp. 1242-1254, May 2022, doi: 10.1109/TMI.2021.3136682.
18. R. Lanzarotti, P. Campadelli and N. A. Borghese, "Automatic features detection for overlapping face images on their 3D range models," Proceedings 11th International Conference on Image Analysis and Processing, 2001, pp. 316-321, doi: 10.1109/ICIAP.2001.957028.
19. B. Ganguly, D. Dey and S. Munshi, "Image Visibility Filter-Based Interpretable Deep Learning Framework for Skin Lesion Diagnosis," in *IEEE Transactions on Industrial Informatics*, vol. 18, no. 8, pp. 5138-5147, Aug. 2022, doi: 10.1109/TII.2021.3119711.
20. A. G. C. Pacheco and R. A. Krohling, "An Attention-Based Mechanism to Combine Images and Metadata in Deep Learning Models Applied to Skin Cancer Classification," in IEEE Journal of Biomedical and Health Informatics, vol. 25, no. 9, pp. 3554-3563, Sept. 2021, doi: 10.1109/JBHI.2021.3062002.
21. L. D. Biasi, A. A. Citarella, M. Risi and G. Tortora, "A Cloud Approach for Melanoma Detection Based on Deep Learning Networks," in IEEE Journal of Biomedical and Health Informatics, vol. 26, no. 3, pp. 962-972, March 2022, doi: 10.1109/JBHI.2021.3113609.
22. S. Albahli, N. Nida, A. Irtaza, M. H. Yousaf and M. T. Mahmood, "Melanoma Lesion Detection and Segmentation Using YOLOv4-DarkNet and Active Contour," in IEEE Access, vol. 8, pp. 198403-198414, 2020, doi: 10.1109/ACCESS.2020.3035345.
23. A. Naeem, M. S. Farooq, A. Khelifi and A. Abid, "Malignant Melanoma Classification Using Deep Learning: Datasets, Performance Measurements, Challenges and Opportunities," in IEEE Access, vol. 8, pp. 110575-110597, 2020, doi: 10.1109/ACCESS.2020.3001507.
24. Md Shahin Ali, Md Sipon Miah, Jahurul Haque, Md Mahbubur Rahman, Md Khairul Islam,” An enhanced technique of skin cancer classification using deep convolutional neural network with transfer learning models”, Machine Learning with Applications, Volume 5, 2021, 100036, ISSN 2666-8270, https://doi.org/10.1016/j.mlwa.2021.100036.

25. Kaur R., GholamHosseini H., Sinha R., Lindén M. Melanoma Classification Using a Novel Deep Convolutional Neural Network with Dermoscopic Images. Sensors. 2022;22:1134. doi: 10.3390/s22031134. - DOI - PMC - PubMed
26. Mohammad Ali Kadampur, Sulaiman Al Riyaee,"Skin cancer detection: Applying a deep learning based model driven architecture in the cloud for classifying dermal cell images",Informatics in Medicine Unlocked,Volume 18,2020,100282,ISSN 2352-9148,https://doi.org/10.1016/j.imu.2019.100282.
27. Dildar M, Akram S, Irfan M, et al. Skin Cancer Detection: A Review Using Deep Learning Techniques. Int J Environ Res Public Health. 2021;18(10):5479. Published 2021 May 20. doi:10.3390/ijerph18105479
28. Jain S, Singhania U, Tripathy B, Nasr EA, Aboudaif MK, Kamrani AK. Deep Learning-Based Transfer Learning for Classification of Skin Cancer. Sensors (Basel). 2021;21(23):8142. Published 2021 Dec 6. doi:10.3390/s21238142
29. Esteva, A., Kuprel, B., Novoa, R. et al. Dermatologist-level classification of skin cancer with deep neural networks. Nature **542,** 115–118 (2017). https://doi.org/10.1038/nature21056
30. Hekler A, Kather JN, Krieghoff-Henning E, Utikal JS, Meier F, Gellrich FF, Upmeier zu Belzen J, French L, Schlager JG, Ghoreschi K, Wilhelm T, Kutzner H, Berking C, Heppt MV, Haferkamp S, Sondermann W, Schadendorf D, Schilling B, Izar B, Maron R, Schmitt M, Fröhling S, Lipka DB and Brinker TJ (2020) Effects of Label Noise on Deep Learning-Based Skin Cancer Classification. Front. Med. 7:177. doi: 10.3389/fmed.2020.00177
31. Chaturvedi, S.S., Tembhurne, J.V. & Diwan, T. A multi-class skin Cancer classification using deep convolutional neural networks. Multimed Tools Appl **79,** 28477–28498 (2020). https://doi.org/10.1007/s11042-020-09388-2
32. Mohammed Rakeibul Hasan, Mohammed Ishraaf Fatemi, Mohammad Monirujjaman Khan, Manjit Kaur, Atef Zaguia, "Comparative Analysis of Skin Cancer (Benign vs. Malignant) Detection Using Convolutional Neural Networks", Journal of Healthcare Engineering, vol. 2021, Article ID 5895156, 17 pages, 2021. https://doi.org/10.1155/2021/5895156