Melanoma Skin Cancer Using Deep Learning Image Processing

Rama Murthy V[a]*, Kiran B S[b], Sachin Rathod[c], Mr. Santhosh Kumar B[d]

[a]*Student, Department of Computer Science and Engineering, New Horizon College of Engineering Bengaluru, India*
[b]*Student, Department of Computer Science and Engineering, New Horizon College of Engineering Bengaluru, India.*
[c]*Student, Department of Computer Science and Engineering, New Horizon College of Engineering Bengaluru, India.*
[d]*Senior Associate Professor Department of Computer Science and Engineering, New Horizon College of Engineering Bengaluru, India.*

Abstract

Skin malignant growth is a significant general medical condition, like the most well-known sort of disease and addresses the greater part of disease analyze around the world. Early discovery impacts the result of the illness and spurs our work. Melanoma is the most deadly one among any remaining skin diseases and the main justification for 77% passings because of skin malignant growth. The most ideal way to lessen these passings is to identify malignant growth at its beginning phases so it tends to be dealt with and relieved with minor treatment or medical procedures. To accelerate and work on the course of early recognition, we propose a programmed grouping strategy for melanoma disease utilizing a high-level profound brain organization. Profound learning models require frightened dataset to work proficiently, however because of restricted time and the weighty responsibility of specialists, there is an absence of commented on skin malignant growth picture. Thus, the proposed model presents ill-disposed preparing for accomplishing better exactness even with a limited quantity of information. The model eliminates pointless subtleties and commotion from the picture and enhances the profundity and slope in the aspects and the shade of the picture. This proposed ill-disposed technique utilizes the slopes of the misfortune regarding the info picture to make a new antagonistic model picture that expands the misfortune for an info picture. The artificially created pictures are utilized in the order framework for preparation and testing purposes. A similar examination of preparing with an ill-disposed approach and without an antagonistic methodology on various pre-prepared models, specifically VGG16, VGG19, Densenet121, and Resnet101, is likewise presented in this work. ResNet101 with ill-disposed preparing has shown a condition of - the - craftsmanship precision execution of 84.77% for melanoma grouping. Accordingly, the proposed approach can be viewed as an effective strategy for characterizing harmless and dangerous melanoma.

Keywords: Deep learning, skin cancer, FGSM, GAN, Melanoma

1. Introduction

Cancer is the uncontrolled division of the cells in the body. These abnormal growths of cells form tissues called tumors. Tumorscanbeeitherbenign(precancerous)ormalignant(cancerous). The tumors destroy the healthy tissues around them. In the later stages, these tumors detach from the original affected location to different parts of the body through the blood circulatory system, which is called Metastases. There are many factors that contribute to the formation of cancer, such as images which are acquired by standard cameras or mobile genetics, chemicals, pollutants, certain foods, and many more. The incidence rate of skin cancer is increasing every year. In 2021, WHO reported that a 22.1% percentage of 1,00,000got affected with malignant melanoma skin cancer. It was also estimated that there might be a spike in melanoma skin cancer cases by 8%. The mortality rate can be reduced by treating the affected patients at the earliest stage possible. Moreover, for this, early detection is very much essential. Computer-aided diagnosis (CADs) helps the doctors to speed up the process and work as an assistive tool[9]. Several researchers have done their fair share of research in skin cancer detection using variously supervised, unsupervised, and semi-supervised learning technology incorporated into CADs systems. Deep Learning techniques perform efficiently in an a Tural image classification task. In this direction, Maglo-giannisetal. Developed a system formula identification to detect melanoma and achieved an accuracy of 77% with SVM.

Gravitas. created an automated global boundary recognition system in dermo scopas images based on color-model depth analysis and global histogram threes holding in the detection of melanoma abrasions. Abdulla Hetal. used an image segregation technique into various clinically significant regions using the Euclidean distance transform to get the color and grain characteristics. Calcaneal. designed a CNN based on Dense Net and exploited it for the automatic recognition of several classes of skin cancer.

* Rama Murthy V
E-mail address: ramnewhorizon.nhce@gmail.com

Demerit al. classified benign or malignant skin cancer lesions with an accuracy of 84.09% using ResNet-101 and 87.42%using Inception-v3. In this work, to enhance the development, we propose a CADs system using deep learning. Our model uses adversarial training of deep learning model with FGS M that allow sour model to detect the noisy images without any difficulty. We use three different classifiers, VGG16, Densenet101, and Resnet, along with FGSM attacks for skin cancer classification.

2. Methodology

This work aims to develop an automatic classification method for melanoma skin cancer, considering the limited availability of the dataset. We have followed different steps to achieve this objective, and they are listed below. The followed steps are discussed in detail in this section.

1) Amplifythedepthandgradientinthedimensionsandshadeoftheinputimage.
2) Extraction of useful information from the amplified and generated images.

***A. Finally*,** this information is used in the classification system or training and testing purposes. *Proposed Method*

In this work, we used two different methodologies and evaluated the comparative analysis of different parameters of the models with GAN and Adversarial training.

i. ***Adversarial training using FGSM:*** We used adversarial training for deep classification. It is a brute force defense against adversarial attacks. Fig. 1 shows the process of ad-versa rial training. Firstly, the normal model in this method generates adversarial images using an FGSM attack, and the same model is again trained on those adversarial images along with the original images, and the final model accuracy is evaluated on both adversarial and normal images. Adversarial training of the model made it more robust and predicted the labels correctly than the actual ones with good accuracy.

ii. ***FGSM Attack:*** It is a brute force adversarial machine learning technique where it creates adversarial samples by using the network gradients. The method takes the input sample and creates the adversarial sample by using the gradients of the loss function with respect to the input one to create new one by considering maximum loss. Adversarial images created from the FGSM attack are used for the adversarial training of our model.

$$p_{adversarial} = p_{original} + sign\,(\Delta\ x\ M\ (\Theta,\ p_{original},\ p_{label})) \quad (1)$$

Where, Where, ϵ denotes the multiplier for achieving smaller perturbations, p_o *original* is the original sample, p_a *adversarial* is the adversarial example, p_l *label* is the label M is the loss function and include parameters of the model. We created per durations with a epsilon multiplier value. The following model developed is used to prevent adversarial attacks aiming at developing an efficient and robust model which can classify labels correctly despite being fed with noisy data.

B. Back ground of the Classifier

Generative Adversarial Network (GAN): GAN is a network that uses generating models via deep learning approaches, for instance, CNN. It is based on unsupervised machine learning, whereby the model is fed data and is trained using a particular dataset. The model learns and discovers patterns and sequences in the input data such that it can generate new results that could initially be predicted from the originally given dataset. GAN is composed of two parts; a generator which is used for the training of new examples, and a discriminator, which is used to identify and classify when the resultant examples are authentic (real) or not (fake). It can be depicted as,

$$E_x[log(D(x))] + E_y[log(1-D(G(z)))] \quad (2)$$

Where D(x) is the discriminator's estimate of the probability that real data instance x is real, and $E_x$is the expected value over all real data instances. G(z) is the generator's output when given noise z. D(G(z)) is the discriminator's estimate of the probability hate fake instance Is real. $E_z$is the expected value over all random inputs to the generator (in effect, the expected value over all generated fake instances G(z)). The formula derives from the cross-entropy between the real and generated distributions.

VGG16: Vgg16 is basically a CNN model having only Conv and pooling layers in it, taking an input of image size224x224x3.Thereare16layersinthismodelwhichholdsomeweights. Our model uses a 2x2 kernel for max-pooling and a3x3kernelforconvolution.

VGG19: Vgg19 is basically a type of VGG CNN model having convolutional and pooling layers taking an input of224x224x3 tensor. There are 19 layers in it with 16 convolutionally, three fully connected layers, five max pool layers, and ones of max layer.

ResNet101: ResNet is a specific type of residual neural network that was introduced in 2015 by Kaiman He teal. To solve a complex problem, we stack some additional layers sin the Deep Neural Networks, which results in improved accuracy and performance. The intuition behind adding more layers is that these layers progressively learn more complex features. The skip connections in ResNet help in solving the vanishing gradient problem. It permits a different route for the gradient to flow through. These connections help by allowing the model to learn the identity functions, ensuring that the higher layer will perform better than the previous layer.

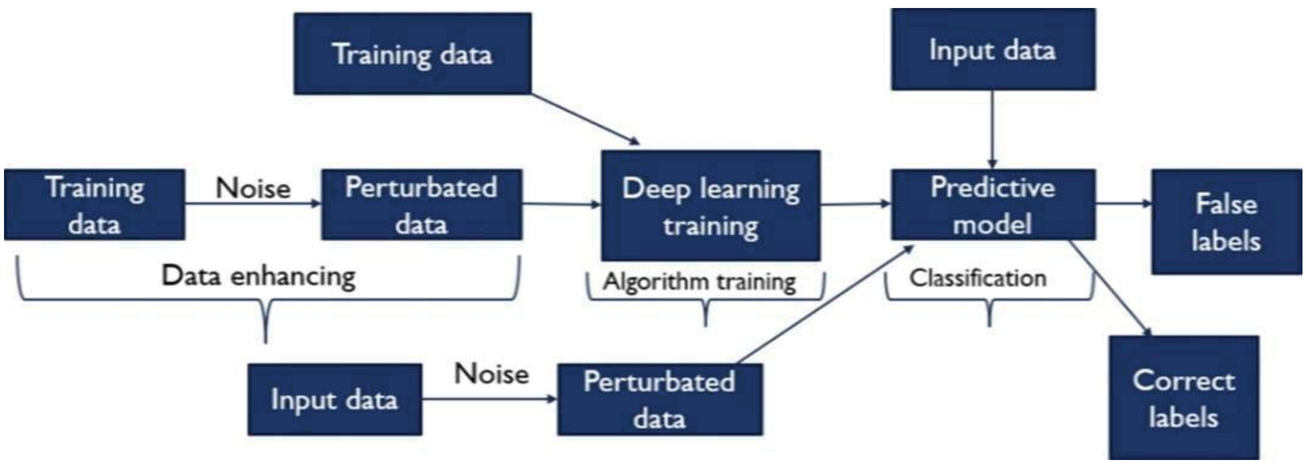
DenseNet: Dense net is a neural network that takes the concatenated input by concatenating the current layer output with the previous layers to achieve maximum accuracy without any loss of data till the final layer.

The composite function is responsible for the concatenation off feature maps of previous layers and feature maps of the latest output layer. The composite function involves the implementation of three functions, namely batch normalization followed by Rectified linear unit followed by $3x$Conv. If we have layers from to and H as the composite function, then the output from the J the layer is the composite operation on the concatenated input formed by concatenating the previous layers with the latest output as follows

$$X_j = H_j([x_0, x_1, \ldots, x(j-1)]$$

C . Dataset

In this work, we have considered a publicly available derma to scopic skin lesions dataset HAM10000. The dataset can be downloaded from the link: ***https://dataverse.harvard.edu/dataset.xhtml?persistentId=doi:10.7910/DVN/DBW86T***. The data set consists of 10015 multisource derma to scope images Fig.2 shows as ample image frame a croft he benign and malignant classes.



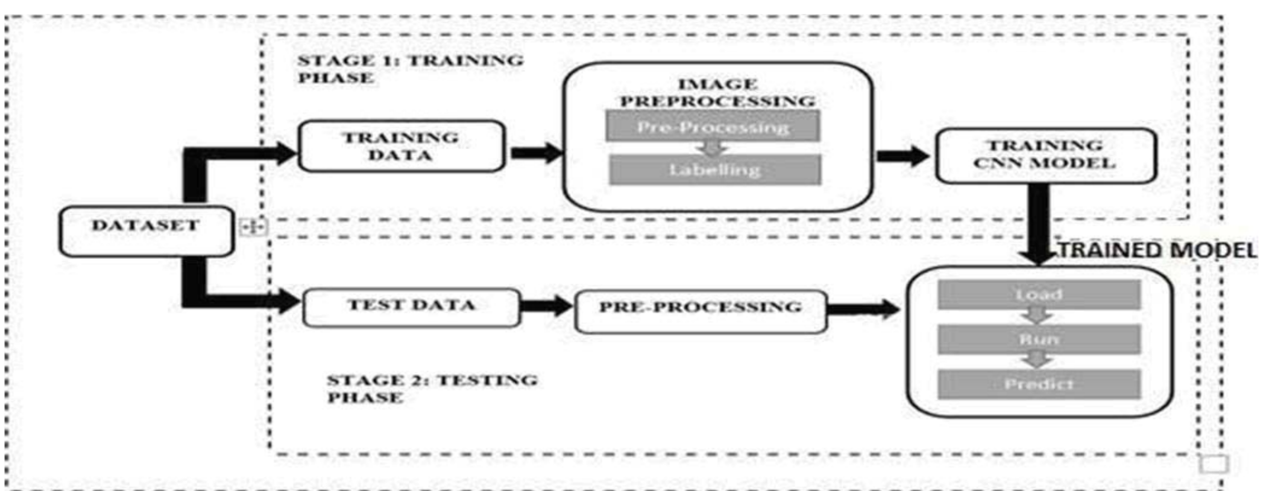


Table 1: Result of GAN on HAM 10000 dataset

Neural network	Accuracy(in %)		Computational time(in sec)	
	Without Adversarial Training	With Adversarial Training	Without Adversarial Training	With Adversarial Training
VGG16	76.3	82.94	583.2875	854.7395
VGG19	75	76.3	1011.618	1184.618
DENSENET121	81.6	82.8	1558.952	1744.7543
ResNet101	83.69	84.77	2986.518	3432.237

3. Results and Discussion

We have evaluated results using the python version 3.7 along with scikit-learn. Accuracy and computational times, along with the confusion matrices, are reported for all the classifiers in Table I. Computational time is the sum of both the training and testing I me taken by the neural network. It is given by the following g equation,

$$T_{ct}=Tr_{ct}+Te_{ct} \quad (4)$$

Where, Tct=Total computational time, Tr_{ct}=Training computational time, Te_{ct}=Testing computational time.

Model	Accuracy(in%)
GAN	74.86%

Table II shows that GAN achieved 74.65% training accuracy at a loss of 0.7543, and while validating the model, it achieved 74.76% accuracy at a loss of 0. 5865. The accuracy, loss curve, and the confusion matrix of GAN trained and tested on HAM10000 are plotted in Fig. 3 ResNet 101 out performs the other model while classifying benign and malignant skin lesions with a training accuracy of 86.67% and testing accuracy of 84.09% with a validation loss of 0.3370.-The computational time of ResNet 101 is 2986.936924 sec.

Discussion:

The benign and malignant lesions a real most similar in appearance, which is difficult for the learning approach to distinguish properly using the similarity function. Despite that, the results show that the classifier with and without adversarial effect does have a negligible difference. Hence, we can comprehend from the result that the ResNet101 can be used to classify benign and malignant melanoma efficiently. The use of FGSM makes the model more robust to noise. Among all the classifiers used in work, Vgg16 is more stable in terms of computational time. Resnet101 is more stable in terms of accuracy but consumes more computational power and computational time with and without adversarial training.

Fig.1. Benign lesion

Fig.2. Malignant lesion

We achieved better results with GAN than the other methods used in this work, but it requires high computational power than other models.

4. Conclusion

This work proposed an overland efficient approach form align ant melanoma detection based on CNN that uses adversarial training for achieving better accuracy even with a small amount of data. As the model remove sun necessary detail sand noise from the image and amplifies the depth and gradient in the dimensions and the shade of the image and synthetically generates images for training and testing purposes, it performs well in presence of noise. The comparative analysis of training with an adversarial approach and without an adversarial approach on different pre-trained models, namely VGG16, VGG19, Densenet121, and Resnet101 shows that ResNet101with adversarial training has shown a state-of-the-art accuracy performance of 84.77% for melanoma classification. Therefore, the proposed approach can be considered an efficient method for classifying benign and malignant melanoma. This work can be considered as baseline work for future research in this direction to improve melanoma detection.

References

1. Mohamed Chingy, Omar Bancshares, “Netflix Recommendation System based on TF-IDF and Cosine Similarity Algorithms,” Research Gate Transactions.
2. Ehtisham Elahi, “Reinforcement Learning for Budget Constrained,” Netflix Tech Blog.
3. Yin Xu, Hong MA, “Research and Implementation of the Text Matching Algorithm in the Field of Housing Law and Policy Based on Deep Learning,” Wiley.
4. Atharva Kulkarni, Tanuj Shankar war, Siddharth Throat” Personality Prediction Via CV Analysis using Machine Learning.”
5. Goel, A.K, Bakshi, R, grawal,K., “Web3.0 and Decentralized Applications”, Mater.Proc.2022, 10,8. https://doi.org/10.3390/materproc2022010008.
6. Saksham Sharma, Avni Bhardwaj, “PROGRESSIVE WEB APPS (PWA),” JETIR July 2021, Volume 8, Issue 7 www.jetir.org (ISSN-2349-5162) JETIR2107594 Journal.
7. Fang, C, Liu, H,” Research and Application of Improved Clustering Algorithm in Retail Customer Classification,” Symmetry 2021,13,1789, https://doi.org/10.3390/sym13101789.
8. Z inah Tareq Nayyef, Sarah Faris Amer, Zena Hussain, “Peer-to-Peer Multimedia Real-Time Communication System based on Web RTC Technology”, International Journal of Engineering & Technology.
9. Matthias Schonlau, Rosie Yuyan Zou, “The random forest algorithm for statistical Learning,” The Stata Journal (2020) 20, Number 1, pp.3{29}.
10. Dr Senthil Kumar, Riya, “Decentralized Storage of Educational Assets Using NFTs And Blockchain Technology, IEEE Explore.
11. Parsi Kalpana, S. Nagendra Prabhu, Vijayakumar Pole ally, Jagannadha Rao D.B, “Exponentially-spider monkey optimization based allocation of resource in cloud,” International Journal of Intelligent Systems (Wiley).
12. Anidha, Suresh, Dinesh, “Analysis of classification and clustering techniques for ambient AQI using machine learning algorithms,” IEEE Explore.
13. Dr. Rajalakshmi B, Babu Aman Singh, Rachit S Kumar, Rohit Harsha, “Rapid Prototype Design with Machine Learning Visualization for Disaster Prediction”, JM.
14. Dr. Rajalakshmi B., B. Anusha, Bindu Madhavi K., B. Lakshmi Keerthi, “Rapid Prototype Design with Machine Learning Visualization for Disaster Prediction”, JM.

15. The future of cybersecurity: Major role of artificial intelligence, machine learning, and deep learning in cyberspace, B Geluvaraj, PM Satwik, TA Ashok Kumar - International Conference on Computer Networks and …, 2019
16. A Naïve Bayes Approach for Predicting the Skin Allergy Diseases, B Geluvaraj, K Santhosh, T Sandhya, V Akshay Reddy… - … and Information Technologies: Proceedings of ICICIT …, 2023
17. A Study on Applications of AI, ML, DL And Blockchain In Healthcare And Pharmaceuticals And It is Future , S PM, B Geluvaraj, TAA Kumar – 2018
18. Saeed, J.; Zeebaree, S. Skin Lesion Classification Based on Deep Convolutional Neural Networks Architectures. J. Appl. Sci. Technol. Trends 2021,
19. Khan, I.U.; Aslam, N.; Anwar, T.; Aljameel, S.S.; Ullah, M.; Khan, R.; Rehman, A.; Akhtar, N. Remote Diagnosis and Tri-aging Model for Skin Cancer Using EfficientNet and Extreme Gradient Boosting. Complexity 2021, 2021, 5591614.
20. Nikitkina, A.I.; Bikmulina, P.Y.; Gafarova, E.R.; Kosheleva, N.V.; Efremov, Y.M.; Bezrukov, E.A.; Butnaru, D.V.; Dolganova, I.N.; Chernomyrdin, N.V.; Cherkasova, O.P.; et al. Terahertz radiation and the skin: A review. J. Biomed. Opt. 2021, 26, 043005.
21. Thamizhamuthu, R.; Manjula, D. Skin Melanoma Classification System Using Deep Learning. Comput. Mater. Contin. 2021, 68, 1147–1160.
22. Reshma, G.; Al-Atroshi, C.; Nassa, V.K.; Geetha, B.; Sunitha, G.; Galety, M.G.; Neelakandan, S. Deep Learning-Based Skin Lesion Diagnosis Model Using Dermoscopic Images. Intell. Autom. Soft Comput. 2022, 31, 621–634.
23. Yao, P.; Shen, S.; Xu, M.; Liu, P.; Zhang, F.; Xing, J.; Shao, P.; Kaffenberger, B.; Xu, R.X. Single model deep learning on im-balanced small datasets for skin lesion classification. arXiv 2021, arXiv:2102.01284.
24. Adegun, A.; Viriri, S. Deep learning techniques for skin lesion analysis and melanoma cancer detection: A survey of state-of-the-art. Artif. Intell. Rev. 2020, 54, 811–841.
25. Reis, H.C.; Turk, V.; Khoshelham, K.; Kaya, S. InSiNet: A deep convolutional approach to skin cancer detection and seg-mentation. Med. Biol. Eng. Comput. 2022, 60, 643–662.
26. Zare, R.; Pourkazemi, A. DenseNet approach to segmentation and classification of dermatoscopic skin lesions images. arXiv 2021, arXiv:2110.04632.
27. Thapar, P.; Rakhra, M.; Cazzato, G.; Hossain, M.S. A novel hybrid deep learning approach for skin lesion segmentation and classification. J. Healthc. Eng. 2022,
28. Polat, K.; Koc, K.O. Detection of skin diseases from dermoscopy image using the combination of convolutional neural network and one-versus-all. J. Artif. Intell. Syst. 2020, 2, 80–97.
29. Bann DV, Chaikhoutdinov I, Zhu J, Andrews G. Satellite, and in-transit metastatic disease in melanoma skin cancer: a retrospective review of disease presentation, treatment, and outcomes. Dermatol Surg. 2019. https://doi.org/10.1097/DSS.0000000000001643.
30. Tschandl P, et al. Human–computer collaboration for skin cancer recognition. Nat Med. 2020. https://doi.org/10.1038/s41591-020-0942-0.