Skin Lesion Analysis towards Melanoma Detection with Deep Neural Network

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***Abstract*—Skin disease is the most widely recognized malignant growth all around the world. including most of skin disease cases with melanoma being the deadliest structure. In the statistic shading pictures of skin, there is high similarity when various skin injury like melanoma and nevus are considered, these increment the trouble of discovery and determination of the skin disease. A dependable computerized framework for skin injury order is basic for early discovery to spare exertion, time and most importantly, human life. In this paper, an automatic skin sore arrangement strategy is proposed. This article depicts the structure, usage, and results of the most recent portion of the dermoscopic picture investigation benchmark challenge. The objective is to help explore what's more, advancement of calculations for computerized determination of melanoma, the deadliest skin malignancy. The technique under consideration here comprise of a pre-trained deep learning system and transfer learning. Notwithstanding calibrating and information enlargement, the exchange learning is connected to a pre-trained model called MobileNet by supplanting the last layer by a softmax to characterize nine distinct injuries (Actinic keratosis, Basal cell carcinoma, Benign keratosis, Dermatofibroma, Melanocytic nevus, Melanoma, Squamous cell carcinoma, Vascular sore, none of the others). The proposed model is prepared and tried utilizing the ISIC 2019 dataset. The notable quantitative measures like precision, top_2_accuracy and top_3_accuracy are utilized in assessing the exhibition of the proposed technique where the acquired estimations of these measures are 77.70%, 92.02% and 98.93% separately. The exhibition of the proposed technique is contrasted and the current strategies where the order rate of the previous beat the presentation of the last strategies.**

Index Terms—Dermatology, Dermoscopy, melanoma, skin cancer, lesion segmentation, Disease classification, feature detection algorithm, deep learning, transfer learning, MobileNet, dataset, softmax, f1 score.

1. INTRODUCTION

One of the most dangerous disease that continues to challenge mankind is cancer. It can be best described as the uncontrolled division and growth of cells in a living thing. Cancer is of many types but skin cancer is considered to be one of the prominent and troublesome among all the other.

Skin malignancy, uniquely melanoma is one of most lethal sicknesses. Bright (UV) light from the sun is the primary driver of most skin diseases. UV light harms the DNA (hereditary material) in our skin cells and can cause skin disease. Being exposed to a lot of sun or getting sunburnt as a youngster are significant hazard factors for creating BCCs or SCCs.

BCC is ordinarily moderate and frequently limited to the skin, with a general metastatic rate of under 0.1%. Cutaneous SCC, strikingly, has 0.3–3.7% of general metastatic rate these rates are following higher trends for explicit zones, for example lips and ears. Two of the majors set up risk factors for NMSC are an individual history of steady splendid radiation (UVR) presentation and a family heritage of NMSC. The risk factor is impacted by the lifestyle choices made by the individual, incorporating a past loaded up with smoking and usage of tanning salons that can expand the threat of SCC by a factor of 2.38 and 2.59, separately. Melanoma is only one sort of skin malignancy. Although less occurring than BCC or SCC, Melanoma is considered to be risky on the basis of its spread. Its growth is not lesion specific which makes it more dangerous. In case of men, it is well on the way to influence chest and the back. When it comes to ladies, the most common recognized sites are legs. Neck and face being other regions of effect.

Around 5 million new instances of skin malignant growth are recorded in the United States of America each year. One of every five Americans will be determined to have a cutaneous threat in their lifetime. In spite of the fact that melanomas speak to less than 5% of all skin malignant growths in the United States, they represent roughly 75% of all skin-disease related passing, and are in charge of more than 10,000 passing every year in the United States of America alone. Early identification is basic, as the assessed 5-year survival time period for melanoma skin cancer drops from 99% whenever recognized in its most punctual stages to around 14% whenever distinguished in its most recent stages.

The recent statistics from WHO in 2015 reveals the total population across the globe who are affected by various skin lesions is referred below in Fig 1.1

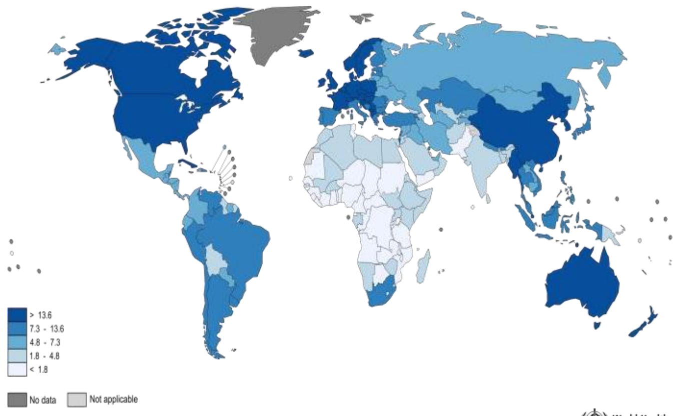

Fig 1.1 Statistics on Skin lesion growth from World Health Organization [10]

Deep Learning has become a very important technology of late and is one of the most sought out approaches for tackling medical challenges. Support Vector Machine (SVM), sparse coding and a deep learning methodology when combined resulted in a classification accuracy of 93.10%, according to Codella [1]. Artificial Neural Networks (ANN) also proved to be of good efficiency as Ozkan and Koklu developed a skin lesion classification system where they associated multiple AI systems to gather infection into melanoma, unpredictable and normal [2]. This resulted in a highest accuracy of 92.50%. Multi-scale lesion-biased representation (MLR) and joint reverse classification (JRC) were worked on by Bietal who put forth a melanoma revelation structure [3]. The obtained precision came out be 92% when the notwithstanding the injuries were classified into melanoma and non-melanoma. Premaladha proposed a melanoma portrayal structure that improves pictures by separation confined flexible histogram leveling methodology, and a short time later, the isolated dull scale picture was partitioned by standardized system for Otsu [4]. The classification precision using significant learning was 92.89%. Here, a deep convolutional neural framework (DCNN) is associated which describe shading pictures harmful development of skin into three sorts: Melanoma, a typical nevus, and customary nevus. This proposed system has two essential central focuses in the past PC supported strategies for skin dangerous development. At first, the proposed technique can work with an image. Secondly, this technique doesn't need any preprocessing as it tends to work fine for shading pictures of skin.

2. Related Work

I. In this area, the accentuation is on applying different systems for skin malignant growth location and finding, with additional concentrate on the ongoing examinations that have utilized profound learning for a similar reason. A computer-aided supported way to deal with the identification of skin malignancy is proposed [5]. Enabling the feature extraction using CNN's by Dubal et al to perceive the affected skin pictures without coordinating segment extraction and division independently [6].

An efficient and sophisticated framework has been utilized for implementing the convolutional neural network (CNN) system [7]. convolutional neural networks were used as feature extractors, whereas ANN's for classifying the removed features. Classifiers such as SVM or KNN were not used as they were too basic for the convolutional neural network (CNN) model that implemented the classification by three totally related layers. Ali and Al-Marzouqi used trade making sense of how to change the building of a convolutional neural network (CNN) inside the LightNet pre-trained model for increasing accuracy [8].

We had gone through two approaches during our research work. One with training the model with augmented images and the other approach is without any data augmentation. The second approach, i.e. training the model without data augmentation resulted in over-fitting when tested with multiple pre-trained models. The first approach, i.e. training the model with data argumentation has performed better than the previous approach.

This convolutional neural network (CNN) model performed superior to the above portrayed techniques as far as accuracy and sensitivity are considered and the proposed this model has numerous favorable circumstances, for example, lesser computational multifaceted nature and preferable speculation ability over different models.

3. METHODOLOGY

The basic intention of creating an innovative convolutional neural network (CNN) model is to classify mentioned skin cancer types and is more inclined towards melanoma detection. This convolutional neural network (CNN) model was readied with deromgraphic images made available by ISIC. Here, few convolutional neural network (CNN)structures were made by fluctuating parameters and after comparing the different structures, the one with the best precision was adopted.

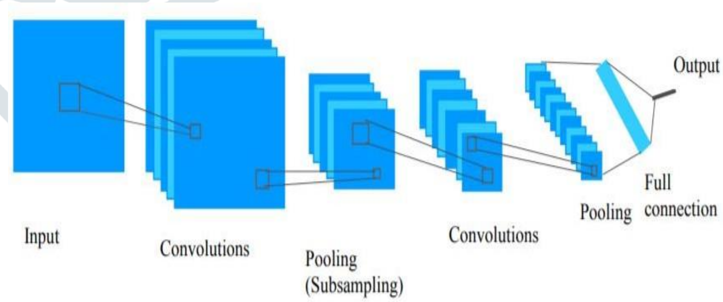

Fig 3.1: Representation of convolutional neural network (Haley, 2015) [9]

To realize the best suitable model for our classification challenge we implemented our code by using some pretrained models. The obtained accuracy from the respective pretrained model are listed below

Pre-Trained Model	Accuracy
NASNet	0.413
ResNet	0.511
InceptionResNetV2	0.563
VGG16	0.652
MobileNet	0.779

Table 3.1 Data of Accuracies obtained from various pre-trained model

From the analysis conducted, we chose MobileNet model as the best suited one for our criteria. This design utilizes depth-wise divisible convolutions which altogether diminishes the quantity of parameters when contrasted with the system with typical convolutions with a similar profundity in the systems. This outcomes in light weight profound neural systems. By default, MobileNet comes with a depth of 47 layers to extract the features of the dataset. Since this pre-trained model were not trained with medical Dermoscopic images by the time, we removed the last certain number of layers and replace with some dense layers. We removed the last six layers from the respective pre-trained model and we added the dense layer with eight nodes and we used softmax as our activation function to classify the input image into one of its respective targeted classes.

4. Experimental Results

Dataset:

The images and metadata of the ISIC 2019 Training data are used to train our model. There are 25,331 images available for training across 8 different types namely Actinic keratosis, Basal cell carcinoma, Benign keratosis, Dermatofibroma, Melanocytic nevus, Melanoma, Squamous cell carcinoma, Vascular sore.

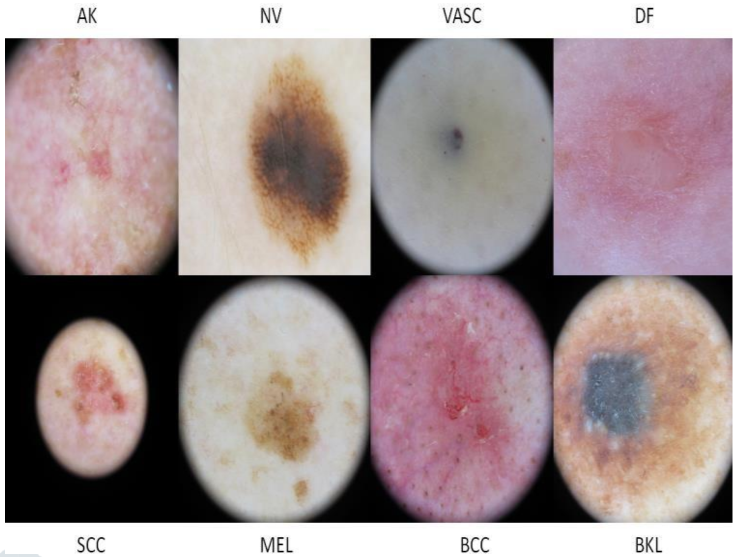

Fig 4.1 Eight Categories of Skin lesion images provided in the dataset

The images have different sizes from hundred to thousand, and the ratio of width and height is various. While exploring the data we faced the imbalanced classes issue which reflects the unequal distribution of images to the targeted classes in the dataset itself. In our case the data distribution on respective targeted classes are represented in a bar graph below

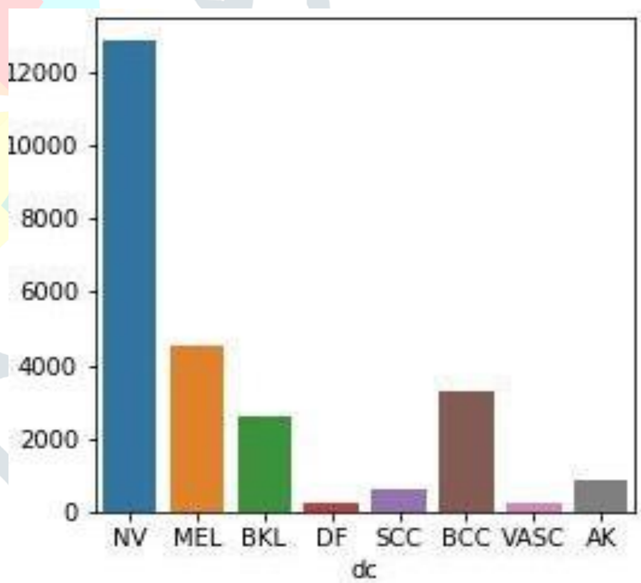

Fig 4.2 Graph of Distribution of Data over eight Categories in the Dataset before Data Augmentation

NV- Nevus	MEL-melanoma
BKL- Benign keratosis	DF- Dermatofibroma
SCC- Squamous cell carcinoma	BCC- Basal cell carcinoma
VASC- Vascular lesion	AK- Actinic keratosis

Pre-processing:

We have performed data pre-processing to improve the performance of our method. As the data suffers from the imbalanced classes issue, we choose data argumentation technique to compensate the underfit and overfit issues while training the pretrained model.

A convolutional neural network (CNN) requires monstrous number of pictures in order to prepare and test for accomplishing high classification rates. This particular scarcity of dataset is a major test when skin malignant growth datasets are considered where the quantity of accessible labeled pictures for preparing and comparing are restricted.

In data augmentation we have done rotation, horizontal flip, vertical flip, zoom, width and height shift for the input images. Images are resized to 224x224.

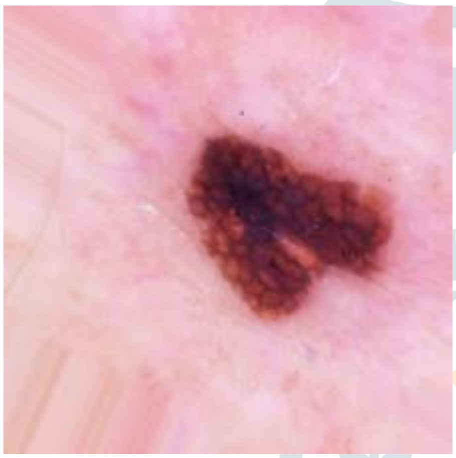

Fig 4.3 Resized Image from the original Dataset

After the data-augmentation is performed, most of the imbalance crisis are eliminated. The distribution of the final data is represented with the help of the graph below.

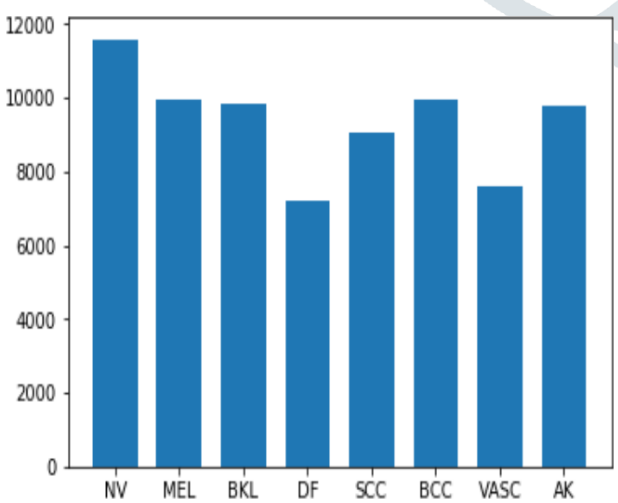

Fig 4.4 Graph of Distribution of Data over eight categories in Dataset after Data Augmentation

NV- Nevus MEL-melanoma
BKL- Benign keratosis DF- Dermatofibroma
SCC- Squamous cell carcinoma BCC- Basal cell carcinoma
VASC- Vascular lesion AK- Actinic keratosis

Training with Transfer Learning:

Preparing a new convolutional neural network (CNN) model required countless pictures. Tragically, no accessible dataset of skin cancer classes with a huge number of marked pictures are available opensource. The hypothesis of transfer learning would be an important answer for solving this difficult issue as a major size therapeutic dataset, for example, the ImageNet can be utilized in pretrained model such as MobileNet.

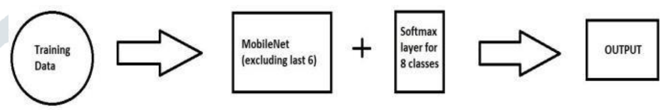

Fig 4.5 Representation picture of the Implemented Model

Two methods were implemented for the proposed model of approach, transfer learning on MobileNet: Firstly, the last layer used for classification has been displaced with a new softmax layer to arrange the data pictures a drastically small number of nine classes when compared to the default 1000 classes in ImageNet. Secondly, the back-propagation procedure has been used for a certain number of layers to align the weights to describe skin cancer classes in an unrivaled manner. A small learning has been used initially, so that the weights of convolutional layers won't radically change while the weights of totally related layers are heedlessly instated. The weights are revived using stochastic gradient descent (SGD) estimation subject to the dataset pictures.

No of Epochs	Categorical accuracy	Top_2_accuracy	Top_3_accuracy
01	0.6613	0.8266	0.9093
10	0.7359	0.9008	0.9605
20	0.7774	0.9185	0.9718
30	0.7730	0.9198	0.9698
40	0.7758	0.9218	0.9694
50	0.7782	0.9202	0.9702
60	0.7770	0.9202	0.9698

Table 4.1 Various metric values obtained from the implementation of transfer learning

We used Adam as optimizer and the learning rate was set to 0.01. Learning rate is reduced as it stagnates using ReduceLROnPlateau. The batch size \is 80. The total epoch is set to 100. We early stop the training when the net starting overfitting.

System Implementation:

Implementation is done by using *nvcr.io/nvidia/tensorflow:17.11* in GNU/Linux 4.15.0-48-generic x86_64 version. We use two Nvidia Tesla GPU's.

Implementation methods:

1. Model Training without data augmentation.
2. Training the model with additional images that are the result of various augmentation techniques.

Experimental Results:

Following graph depicts the validation accuracy and training accuracy obtained by choosing MobileNet as our pretrained model. This graph is drawn between Categorical Accuracy (Y-axis) and Number of Epochs trained (X-axis)

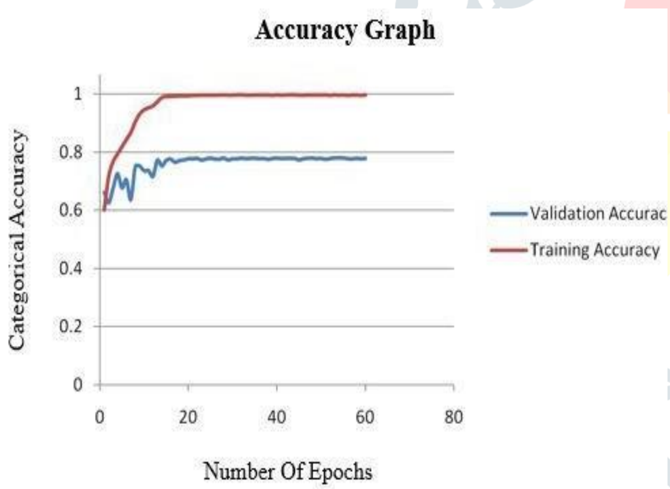

Fig 4.6 variation of validation and training accuracies with increase in number of epochs

5. Conclusion

An enormous number of named pictures are required to produce an efficient and high performance deep neural network. Trade learning and picture expansion are associated with a pre-trained MobileNet to vanquish this genuine test. The proposed strategy can portray eight novel classes by superseding the last layer to softmax with eight hubs in a manner of speaking. According to transfer learning concept, the weights of the altered model are changed notwithstanding the expansion of the dataset pictures.

Three execution measures have been processed for the proposed model to contrast the existing strategies where their outcomes demonstrated better results. The accomplished rates are 77.70%, 92.02% and 96.98% for accuracy, top_2_accuracy and top_3_accuracy respectively.

6. References

1. N. Codella et al., "Deep learning, sparse coding, and SVM for melanoma recognition in dermoscopy images", LNCS, Springer, vol. 9352, pp. 118–126, 2015. Available: *https://doi.org/10.1007/978-3 319-24888-2_15*, Accessed: 15 Aug 2018
2. Ozkan, and M. Koklu, "Skin Lesion Classification using Machine Learning Algorithms", Intelligent Systems and Applications in Engineering, vol. 5, no. 4, pp. 285-289, 2017.
3. L. Bi, J. Kim, E. Ahn, D. Feng, and M. Fulham, "Automatic melanoma detection via multi-scale lesion-biased representation and joint reverse classification", 2016 IEEE 13th Int. Symposium on Biomedical Imaging (ISBI), pp. 1055-1058, 2016.
4. Premaladha, J., and K. S. Ravichandran. "Novel approaches for diagnosing melanoma skin lesions through supervised and deep learning algorithms." Journal of medical systems 40.4 (2016): 96
5. R. B. Aswin, J. A. Jaleel, and S. Salim, ''Hybrid genetic algorithm— Artificial neural network classifier for skin cancer detection,'' in Proc. Int. Conf. Control, Instrum., Commun. Comput. Technol. (ICCICCT), Jul. 2014, pp. 1304–1309.
6. P. Dubal, S. Bhatt, C. Joglekar, and S. Patil, ''Skin cancer detection and classification,'' in Proc. 6th Int. Conf. Elect. Eng. Inform. (ICEEI), Nov. 2017, pp. 1–6.
7. M. Rehman, S. H. Khan, S. M. D. Rizvi, Z. Abbas, and A. Zafar, ''Classification of skin lesion by interference of segmentation and convolotion neural network,'' in Proc. 2nd Int. Conf. Eng. Innov. (ICEI), Jul. 2018, pp. 81–84.
8. A. Esteva et al., ''Dermatologist-level classification of skin cancer with deep neural networks,'' Nature, vol. 542, no. 7639, pp. 115–118, 2017.
9. Harley, A. W. (2015). An interactive node-link visualization of convolutional neural networks. In International Symposium on Visual Computing (pp. 867–877). Springer. Retrieved from http://link.springer.com/chapter/10.1007/978-3-319-27857-5_77
10. Statics image from the data source: GLOBOCAN 2012From WHO in 2015.

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