FOREX Publication
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International Journal of Computer Science Research (IJCSR)
-------------- Article | Volume 3, Issue 3 | Pages 105-108| ISSN XXXX-XXXX

Early Melanoma Detection and Classification Using CNN and Confusion Matrix Analysis

Dinesh Kumar K[1], Vennila G[2], Shanthi H J[3], Balamurugan S[4], Govindharaj I[5] and Manikandan K[6]

[1,5]Vel Tech University, Chennai, India
[2]Mohan Babu University, Tirupati, India
[3]Hindustan Institute of Technology and Science, Chennai, India
[4]JAIN (Deemed-to-be University), Bengaluru, India
[6]AMET University, Chennai, India

***Correspondence:**

ABSTRACT- This article brings up a new method for detecting and classifying skin cancers using Convolutional Neural Networks (CNN) and Confusion Matrix analysis. The main work of this work evolves around detection of Melanoma and Non-Melanoma cells. The large dataset on skin cancers is used to teach the CNN model to accurately classify different types of skin lesions into different malignant and non-cancerous groups. The integration of Confusion Matrix, in this case, allows for accurate identification of the classification errors made by the model as well as possible areas for improvement hence making it possible to comprehensively evaluate how well the model performs. Therefore, early recognition is indispensable to successful treatment as skin cancer is a typical yet fatal condition. Results shows that the suggested proposed model achieves 95.5% accuracy and performance in comparison with other methods found in literature. Additionally, Modified DenseNet201 model has a sensitivity of 95.96% as well as a specificity of 98.03%.

Keywords: Convolutional Neural Networks, Confusion Matrix, Skin Lesions, DenseNet201, Skin cancer, Melanoma Detection.

ARTICLE INFORMATION

Author(s): Dinesh Kumar K, Vennila G, Shanthi H J, Balamurugan S, Govindharaj I and Manikandan K;

Received: 03/08/2024; **Accepted**: 15/08/2024; **Published**: 15/09/2024;
e-ISSN: XXXX-XXXX;
Paper Id: IJCSR-030303;
Citation: 10.37391/IJCSR.030303

Crossref member CROSSREF.ORG THE CITATION LINKING BACKBONE

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1. INTRODUCTION

Deep learning models for melanoma detection and classification brings together modern technology and novel practices in healthcare. This research work would be based on TensorFlow Lite and MobileNet architecture to come up with a Convolutional Neural Network (CNN) algorithm which is efficiently deployable on mobile devices. Our Strategy will revolve around CNNs due to their image classification efficiency when applied. Thus, the best lightweight model for Smartphone deployment is Mobilenet which is an embedded and mobile device specific architecture that balances between size of the model and accuracy. To this end, the approach of this paper involves training the MobileNet CNN model using a carefully selected dataset of benign and malignant lesion photos. The pre-trained MobileNet model will be optimized using transfer learning techniques specifically tailored for our skin cancer classification task. For instance, by examining confusion matrix which is aimed at understanding how good or bad currently chosen classifier may have performed prior to implementing it in ML code, you can analyze different aspects of predictive performance. It also reveals how well the model can accurately distinguish between melanoma, squamous cell carcinoma, basal cell carcinoma nevus among others or it could show things went wrong while building this system. Throughout the whole process of skin cancer diagnosis, a doctor must do several things. In the first stage, 5 mm or bigger lesions are investigated with the assistance of the bare eye. Dermoscopy is applied to obtain more detailed information about the pattern of skin lesions. In this procedure, a gel is spread unto the affected skin area that is easy to ooze out and check for the skin lesion with the help of a magnifying glass [1]. A biopsy is the process of carrying out a removal of part of the skin which is assumed to be abnormal and then using a microscope to examine it further. Some of the specialists diagnose the skin lesion referring to a specific method in their determination known as the ABCDE method that covers aspects such as the color of the lesion, the boundary, the asymmetry, the diameter, and the changes in the lesion over a given period of time [2]. But the actual efficiency of the dermatologists and the clinical facilities only will dictate the result of the inspection. It is worth stating that cancer and particularly skin cancer can be cured and stopped from progressing to the other stages if it is detected earlier. Also, early detection of skin cancer reduces the numbers of expensive medical procedures and the mortality rate [3].

2. RELATED WORK

Skin cancer consisting of Melanoma and Non-Melanoma is a common illness that can prove to be fatal. Such is the case since early detection of the diseases enhances treatment results and rates of survival. Routine diagnostic procedures like clinical examination, dermoscopy, and histopathology are rely on the observer's performance and experience. Thus, the introduction of artificial intelligence (AI) and deep learning is another

International Journal of
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effective solution that allows for the diagnosis of diseases to be made using objective, efficient, and accurate methods. Some of the public datasets that have been used in the creation of deep learning algorithms in skin cancer prediction include the following. Some of the popular publicly available skin lesions databases are the International Skin Imaging Collaboration (ISIC) archive which contains one of the largest collections of dermoscopic images [3]. The dermoscopic images of PH2 are collected from the clinical database and labeled by the professional dermatologists which makes it more authentic to train and test the models [4]. The Dermofit Image Library 'includes more than one thousand high quality/hi-quality images of various skin diseases allowing the training of more robust models [4] [5]. Convolutional neural network, or CNN for short, is perhaps the most popular architecture used in skin cancer detection which performs almost as well as a dermatologist in classifying skin lesions. Three studies by Esteva et al [6] showed that a CNN can achieve error rate of 4.58% on more than 129,000 clinical images of skin cancer, which does not differ much from dermatologists. Fine-tuning a CNN that is originally trained on a large dataset such as ImageNet is useful when the size of the specific dataset on which the CNN is to be fine-tuned is small [7]. Image manipulation procedures like rotation, flipping and scaling are used to diversify data that are used to train deep learning models so as to reduce and avoid overfitting by improving the models' robustness [8]. Ensemble learning, in particular, other models so as to enhance the accurate prediction of outcome results in the decrease of variance and biases of initial models and provides more solid and fruitful classifications [9]. There is some steps with open issues, such as data imbalance in which malignant cases are far less than benign ones, an aspect that can be handled with oversampling, under sampling, and synthetic data. Counterpart, due to the complexity of deep learning models, they are described as 'blackbox', and therefore, measures are being taken towards explanation of models and extracting information regarding features learnt by the models [10]. Furthermore, models learned from datasets could deteriorate on different population or imaging setting thus, cross-dataset validation and domain adaptation methods to create models that can be used on different datasets and can be generalized must be used [9] [10].

3. MATERIALS AND METHODS

A new classification system is provided in this section for the categorization of skin lesions. The framework proposed here has the ability to distinguish cancerous and non-cancerous lesions with the help of deep learning models. The framework needs some steps in the efficient classification of lesions. This is followed by a sequence of steps to retrain the deep learning model that begins with the process of data augmentation of the available dataset followed by transfer learning, fine tuning of the model and the tuning of the hyper parameters of the model. The fine-tuned model successfully obtained computational features as needed for the machine learning classification of melanoma skin cancer lesions. Two siblings of deep learning are employed in this analysis. The augmented dataset is applied for the fine-tuned deep learning model in regard to the needs of this work. The general work flow of the proposed framework is shown in the Figure 1 below which applies various filters in order to select and filter required handicap data. In the following subsections, end-to-end details of each of the proposed workflow steps are given. The first step encompasses identification of appropriate datasets. And one kaggle dataset known as ISIC, which is consisted of photos of skin lesions with labels concerning the type of lesion (neavus, actinick keratosis, pigmented benign, squamous cell carcinoma, basal cell carcinoma, melanoma, vascular lesion, and dermatofibroma).

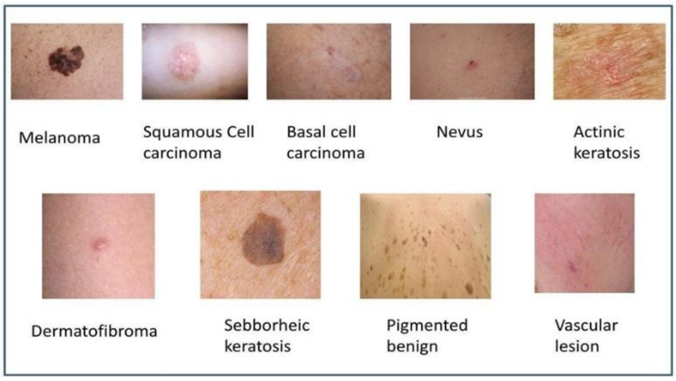

Figure 1. ISIC Data Set

Convolutional Neural Networks, or CNN for short, belongs to a class of deep learning algorithms that are developed to address the core problem of image recognition and classification. Such neural networks consist of several layers, including convolutional, pooling and fully connected layers in a hierarchy to identify features from the input images and to pass the final decision. Confusion matrix was utilized as a key appraisal measure and it is very constructive while assessing the performance of the deep learning model employed in the mobile application for skin cancer detection and classification. For all classes, it offers an additional explanation of how the model predicts something and explains it concerning labels that represent the tested object's true type. Most of the time it's presented in a tabular form with rows representing the actual classes and the columns, the predicted classes.

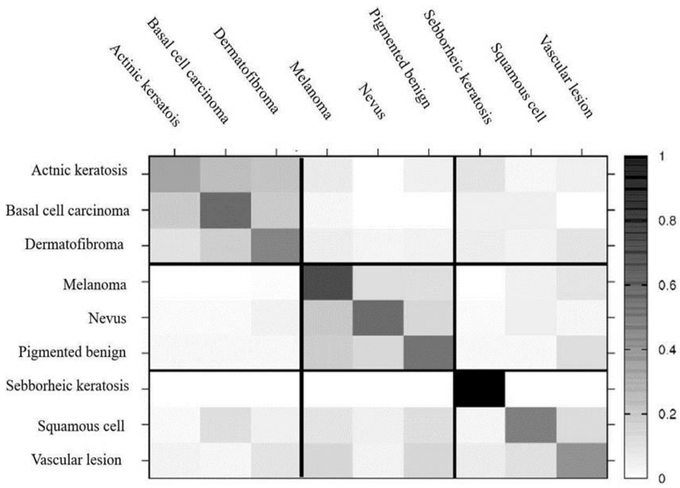

Figure 2. Confusion Matrix

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Each cell of the matrix depicts the count (or proportion) of cases that falls into a particular category. The confusion matrix provides valuable information concerning the performance of the model in connection with diverse forms of skin lesions like squamous cell carcinoma, basal cell carcinoma, melanoma, nevus, actinic keratosis in the case of skin cancer identification and categorization [11].

MobileNet further helps in efficient skin cancer detection using mobile applications as it is a light weight deep learning architecture optimized for mobile operating systems. It theoretically ensures the ability to make rapid inference and has minimal computing load; thus, it is useful in real-time interpretation of skin lesion photos captured using smartphones. MobileNet helps mobile applications to perform skin cancer detection in a more accessible and efficient way, which in turn increases the patients' intervention time and improves the results.

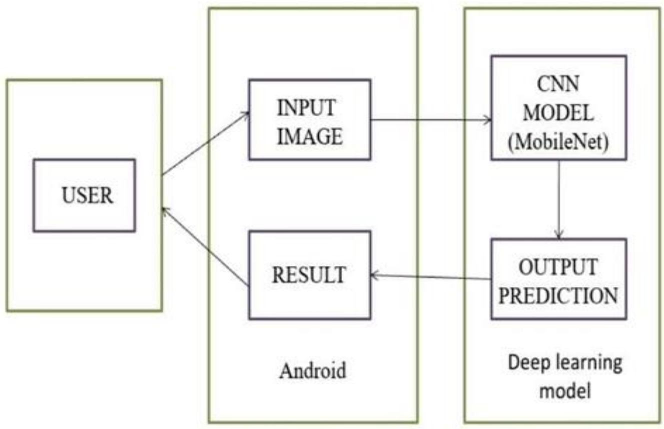

Figure 3. Proposed Architecture

The user begins the architecture by feeding an image of the skin lesion to the system. Following that, another supervised learning model for image classification, a Convolutional Neural Network (CNN) specifically MobileNet is passed through this image. Next, based on such results obtained after post-processing the image the CNN model captures the necessary features indicative of the skin lesion characteristics of an image. The model then gives an output prediction, which is often an approximation of the lesion, a probability that the lesion is benign or cancerous and possibly a confidence score. This preliminary prediction is then followed by an interpretation of the classification task's ultimate outcome. Finally, the user is displayed the result which provides detailed information on the nature of the skin lesion and plays the most significant part in the accurate diagnosis and decision-making process.

4. RESULTS AND DISCUSSIONS

The skin cancer detection and classification mobile application created in this study with the help of TensorFlow Lite, MobileNet, and CNN algorithm showed high results. The confusion matrix indicated a good level of accuracy through the equal number of the benign and malignant lesions that were correctly classified. The measures of precision and recall also consist to prove the capability of the proposed model to correctly detect, not only type 1 but also type 2 of the lesions, if reduced misdiagnosis is the goal in the real clinical application. At the same time, it is critical to be conscious of any drawbacks like variations in the corresponding diversity and image quality of the dataset even if the shown outcome is quite inspiring. Additional studies on content validation with absolute bigger populations and various kinds of people would help AAD strengthen the model's efficiency, especially with regards to skin tone and ethnic variation. However, the developed smartphone application can aid in the preliminary screening and classification of skin cancer that could improve the diagnosing processes and therapeutic judgment in doctors. The results of the diagonisis also be stored in the distributed network using blockchain technology for the future reference. This enables the researchers and doctor to track and verify the patient history through blockchain interface.

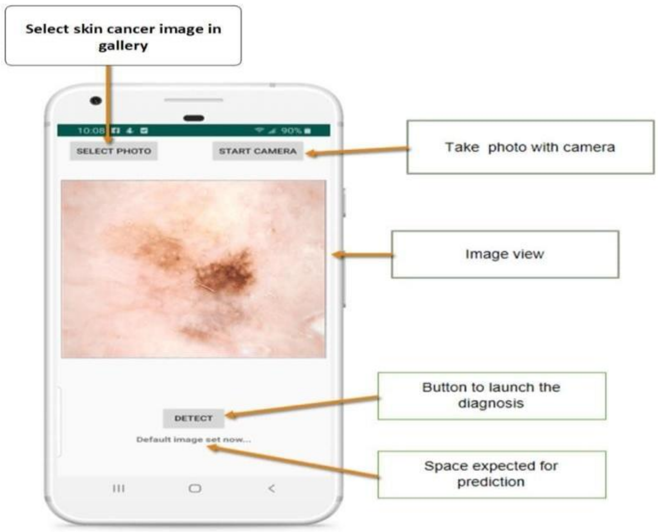

Figure 4. Mobile Application to diagonise the skin tone

The results in this subsection will be presented at the basis of comparison between the results obtained using the innovative technique to the original pre-trained models. Finally, it also contrasts the outcomes of the existing techniques in the literature for skin cancer classification.

As depicted in the following figure, the accuracies attained using different models used in this work is as follows: *Figure 5* From the observation, it is found that both the proposed in this research article Modified MobileNetV2, Modified DenseNet201 were superior than the original pre-trained MobileNetV2 and DenseNet201 models. Furthermore, based on the findings shown in *figure 5*, the Modified DenseNet201 gives higher accuracy than the other three models. This work then situates the proposed technique to the existing techniques available in the literature about the classification of skin cancer. Therefore, it can be concluded that the proposed technique is exemplary for failing to finds its competitor techniques, which provide a 95 percent success rate.

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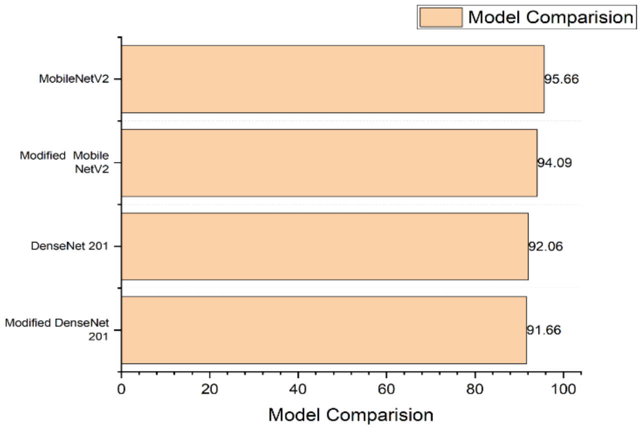

Figure 5. Performance Comparison of four models

5. CONCLUSION

In conclusion, there have been encouraging results from the use of a CNN algorithm and a deep learning model—specifically, the MobileNet architecture—in a mobile application for the identification and categorization of skin cancer. We saw a significant degree of accuracy in differentiating between benign and malignant lesions by using a confusion matrix. This demonstrates the potential of these advancements to facilitate timely identification, offering essential support to healthcare providers in effectively diagnosing and treating patients in a timely manner. It is imperative to acknowledge that further research and validation are necessary, especially when considering differences in image quality and dataset diversity, to ensure the accuracy and reliability of these mobile applications in enhancing patient care.

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