

# Automated Skin Cancer Detection Using an Advanced Deep Learning Approach

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**Abstract** - Melanoma is a skin cancer and it is one of the emerging health concerns to the world with the probability of early diagnosis maximizing the treatment option of choice. Manual examination is often subjective and prone to error whereas the diagnostic examination technique mostly relies on the visual examination. The opportunities of automated systems are enormous to help dermatologists identify cancerous lesions in an effective and accurate way because of the evolution of medical imaging and deep learning. The system described in this paper will be based on the artificial intelligence-based approach to detect skin cancer, which will involve the methods of deep learning, in which Convolutional Neural Networks (CNN) are trained to identify cancerous and benign skin lesions. A CNN based architecture is supposed to process dermoscopic images and in this scenario, a preprocessing stage has been taken into consideration and this is the RGB color space, and Local Binary Pattern (LBP) to augment the extraction of image features. Also, a reduced version of VGG-16 is used in the classification with a better accuracy than the above methods. These benchmark datasets, e.g. HAM10000 and ISIC, have been experimented and the results indicate that the model has a state-of-the-art performance with an accuracy of over 97% which is higher than any other model. The results indicate that the incorporation of deep learning in skin cancer detection can speed up diagnosis, alleviate the burden on dermatologists, and greatly improve early detection, which could translate to improved patient outcomes.

**Keywords**— *Deep Learning; Skin Cancer; Melanoma; Convolutional Neural Network; Dermoscopy;*

## I. INTRODUCTION

Melanoma is a severe and fatal type of skin cancer and is not normally diagnosed or misdiagnosed with benign skin lesions as demonstrated in Figure 1. Melanoma, according to data of Surveillance, Epidemiology, and End Results (SEER) program, is the sixth most common cause of cancer mortality in the United States. It is the cause of 4% of all cancer deaths and most deaths due to skin cancer which are due to melanoma 6 out of seven. Mortality rate of melanoma has been alarmingly

increasing and the number of deaths is likely to continue increasing as reported in a study in 2021 [1]. It is projected that 106,110 new cases of melanoma will be noted in 2021 around 62,260 men and 43,850 women. Also, an estimated 7,180 will develop melanoma with estimated 4,600 males and 2,580 females. Such statistics suggest the importance of early diagnosis and treatment in order to increase the survival rates and lessen the load of melanoma on the health of the population [2]. Skin cancer is a malignant tumor and is caused by unrestrained increase of skin cells and has emerged as one of the most prevalent kinds of cancer in the world. Skin cancer is a significant health issue with 2-3 million new cases every year. It is also one of the most prevalent forms of cancer in the US and is prevalent in most of the communities in New Zealand, Australia, Switzerland, Sweden, and Norway [3]. Of all skin cancers, melanoma is the only one that is infamous as a fast spreading and deadly cancer to most people. Although only a small portion of all skin cancers is melanoma (7 percent), it is the cause of 75 percent of all deaths due to skin cancer [4].

Melanoma is one of those diseases which have to be caught in its first stages; it has been proved that in case of early melanoma diagnosis over 90 per cent of cases can be cured. However, the failure



Fig. 1: 1 Skin Lesions

to detect the malignancy at an early stage results in reduced survival rates of the cancer to fewer than 50 per cent as the malignancy has already spread to other parts of the body. The most important risk factor of the development of skin cancer is exposure to ultraviolet (UV) radiation and this radiation has the ability of destroying the skin cell DNA. Fair skin, history of sunburns, genetic predisposition, and certain medical conditions, which weaken the immune system, are other risk factors [5]. Pathology of skin cancer generally entails two kinds of tumor cells benign and malignant. The malignant tumors are also reported to invade the surrounding tissues and spread to other body parts unlike the benign tumors, which only invade the surrounding tissues without spreading to other parts of the body, thus necessitating aggressive treatment methods such as chemotherapy, radiotherapy or surgery. The diagnosis of skin cancer has been a clinical examination that is done by trained clinicians who during the examination process; they begin with a visual scan of the suspicious parts of the skin after which they proceed to a dermoscopy or magnification which allows them to make finer observations in the skin and lastly, the procedure of diagnosis may proceed to a biopsy in case of need. The procedure of a diagnosis however is not instant and might not be available to all patients, especially in places that lack trained dermatologists. Subjective clinical judgment may also lead to inconsistency in the correctness of the diagnosis, and the results indicate that even the best dermatologists only manage to make correct diagnoses 80% of the time [6]. To address these problems, and to allow the detection of skin cancer in its early stages, there has been an effort to develop computer-aided diagnostic (CAD) systems which take advantage of the advances in image processing and machine learning. In this case, we consider the HAM10000 dataset which is a huge set of dermoscopic photographs which contain representative samples of pigmented skin lesions, non-malignant and malignant. The dataset is emerging as a benchmark of training and testing machine learning models in detection of skin cancer. We apply VGG model which is a popular deep learning model to improve the diagnostic performance since it has been proven to be successful in image classification. VGG model is based on the deep convolutional neural network (CNN) model which is capable of extracting features and, therefore, may be used in complex dermoscopic images. We also use the Support Vector Machines (SVM) which is a form of classification other than the VGG model. SVM is also said to be effective in the high dimensional space and ability to specify the distinct boundary between different classes of data, which further lends support to the diagnosis of skin cancer. We are also applying a Convolutional Neural Network (CNN) which is an effective deep network that is mostly applied in image recognition tasks. The CNNs have been extensively used in the analysis of medical imaging due to its potential to automatically identify hierarchies of raw images, high capabilities in identifying fine structures and abnormalities in skin lesions. A combination of the models will enable us to develop a strong and accurate melanoma and other skin cancers detection system. These CAD systems attempt to enhance the precision of the skin cancer diagnosis process through the process of automatic analysis of

dermoscopic along with other images of the skin lesions. The performance of these CAD systems can be determined by the ability of these systems to generate valuable information out of color pattern, texture, asymmetry and shape of the skin images [7]. To enhance the accuracy of the classification and make the diagnosis process easier, different machine-learning solutions have thus been suggested and developed. Recent developments in the deep learning algorithms such as convolutional neural networks (CNNs) have transformed medical image processing. CNNs have also performed well in the image classification tasks and thus, are among the most popular types in skin cancer detection. The deep learning models can automatically acquire hierarchical features of raw image data and can be used to classify skin lesions with the ability to be more precise and complex. VGG-16 is another popular CNN architecture based on its effectiveness and ability in a number of image classification tasks because they are highly popular [8]. Despite the success that the CNNs have had, there is still more to be done especially with regards to optimization of network architecture and minimization of the computational complexity. The proposed research tries to improve the VGG-16 architecture by streamlining its architecture by eliminating the convolutional layers that are not necessary in order to reduce the number of parameters in the overall architecture. The efficiency of the computation will be increased through optimization in a way that diagnostic performance is not impaired. Additionally, the presence of the concepts of batch normalization (BN) and global average pooling (GAP) layers will be useful to optimize the model performance without the number of parameters growing. In this paper, we showcase a novel method in the skin cancer detection by using a version of VGG-16 model that has been modified. This research is founded on high empirical validation on International Skin Image Collaboration (ISIC) database which is a standard on which the capability of the skin cancer detection algorithms are gauged. We believe the quality of classification is much greater than the traditional methods, and our discovery opens up the potentials of our approach to transform dermatology and patient care radically. The rest of the paper is as follows: Section 2 gives a discussion of related works in the field of skin cancer detection which illuminates on the existing methods and their limitations. Section 3 outlines the proposed methodology, such as architectural changes to the VGG-16 model and experimental setup that were implemented in the course of testing. Section 4 discusses the results of our experiments such as performance measures of our improved model. Finally, Section 5 will be the end of the paper that will summarize the key findings, and provide the perspective on the future research on skin cancer detection.

## II. LITERATURE REVIEW

Skin cancer, particularly melanoma is a significant health risk in the world with a higher risk being caused by a lot of things such as exposure to UV radiation and hereditary factors. Correct diagnosis and classification of skin cancer at an early stage should be carried out to enhance the survival and treatment outcome. The latest innovations in artificial

intelligence (AI) through machine learning (ML) and deep learning (DL) have been promising in increasing the precision and effectiveness of skin cancer diagnosis. Skin illness is brought about by infection and bacteria. Different methods have been used to detect such conditions in their initial stages using image analysis. To assist the researcher to choose the most appropriate way of diagnosis to suit his/her needs, a literature review has been carried out to study how plant and human skin diseases can be diagnosed. Additionally, various approaches are compared and contrasted like color-based image retrieval, expert systems and case-based reasoning methods and are evaluated based on accuracy, reliability, speed, scalability and readability of the results [9]. The other proposed a hybrid system using Convolutional Neural Networks (CNN) and Support Vector Machines (SVM) in order to detect skin cancer. They made comparisons between the performance of their method in various images and other algorithms, including Genetic Algorithms, Artificial Neural Networks (ANN) and SVM. They discover that the proposed technique was able to detect things more accurately by 3.21 percent [10]. The other kind of author that was employed to differentiate human skin cancer was that of Deep Neural Networks. Experiments were conducted on various pictures and three-way and nine-way classification was used. The Convolutional Neural Network (CNN) was trained on a set of data (129,450 clinical images). Their technique was capable of detecting cancer in the pictures with a good degree of success [11]. To assist in the early diagnosis of skin cancer and to overcome some of the challenges discussed earlier, much research has been conducted to develop the up-to-date algorithms in the field of computer-aided image analysis. The goals of this kind of research are to improve the accuracy of the diagnosis, to shorten the duration of image evaluation and, finally, to improve the results of patients. By implementing the latest technologies and strategies, scientists seek to develop algorithms capable of efficiently handling and analyzing medical imaging data, which will allow them to detect skin lesions more accurately. This introduction is important, since early diagnosis is the most important to successful treatment and it enhances the chance of good health outcome in patients with skin cancer [12]. CNNs have become a ubiquitous architecture of deep learning and specifically image processing and computer vision. They are guided by the visual cortex of the animal and hence are useful in detecting patterns and features in pictures. Due to their high performance and accuracy in a variety of machine-learning tasks, especially on tasks such as image classification, object detection and medical image analysis, CNNs have gained immense popularity and are well-received [13]. The most common forms of diagnosing melanoma and revealing the most important features are the visual examination and observation of the color of the skin. This technique is premised on the analysis of color and surface texture of the skin. Dermoscopy on the other hand improves the detection and classification of

the types of cancer by making them appear and morphologically manifest in a clearer manner [14]. Various models will be presented with image and various models will contain various layers of detection and segmentation and they will see the images and reach to a conclusion that they are having cancer or they are not having cancer. After the extraction of features, a training step is needed in order to learn a model to differentiate between benign and malignant lesions. The Support Vector Machines (SVMs) have been widely applied by researchers because it is a powerful tool and easy to use in coming up with an efficient model. However, in [15] performance comparison was done between K-Nearest Neighbor (KNN) classifier and Artificial Neural Networks (ANN) and ANNs proved to be more accurate than KNNs. This is mainly due to the fact that ANNs learn by iteratively modifying their connection weights, minimizing the difference between the actual output and the calculated output. In the last couple of years the deep learning gained significant momentum in melanoma detection solution, since it enables more complex and precise medical image analysis [8]. The author used an SVM classifier to skin cancer using a CNN-extracted feature having four classes according to the research. They had a dataset of 3,753 images acquired online to train and test their model that reached an accuracy of 94.2% [16]. The author employed an in-depth residual network to classify melanoma spots. They ran their recommended algorithm on the ISBI, MED-NODE and PH2 datasets and achieved 98.5% accuracy on the PH2 dataset [17]. The HAM10000, consisting of seven types of skin lesions, was used to test in other pre-trained neural network models. The images were downsampled to 224 224 pixels and data augmentation was done. A number of pretrained deep learning models have been compared and the highest individual accuracy was displayed by the ResNet50 model. The authors went another step further to improve performance by experimenting with the ensemble approach of combining the ResNet50, VGG16 and DenseNet models and the end result was the overall accuracy of 84 percent [18]. The evolution of the computer-aided diagnosis (CAD) systems in detecting skin cancers and melanoma in particular has been improved as the years go by. To classify the skin lesions, initial attempts employed primarily traditional image processing algorithms to obtain the features, e.g. color and texture analysis procedures. However, more advanced approaches that can considerably improve the accuracy of diagnosis have appeared as a result of the development of machine learning (ML) and deep learning (DL) algorithms. Convolutional Neural Networks (CNNs) have become an important part of the skin cancer detection due to their automatic learning ability and their ability to extract complex information of medical images. On a set of over 120,000 clinical images, [19] trained to identify skin cancer using their deep CNN model. Deep. To classify skin cancer, [20] proposed a hybrid method that combines CNN with Support Vector Machines (SVM). The credibility of both

machine learning and deep learning method was proven as they demonstrated that the hybrid model was better than more traditional methods by 3.21 percent, among which are Genetic Algorithms (GA) and Artificial Neural Networks (ANN).

The manner through which skin cancer is classified by using the residual networks has also been discussed. The ISBI, MED-NODE, and PH2 datasets were used by [21] to evaluate their method for classifying melanoma lesions with deep residual networks. Their approach demonstrated the ability of deep residual networks to enhance the detection of melanoma with a greater accuracy rate of 98.5 percent on PH2 dataset. The role of residual networks in the classification of skin cancer has also been studied [22]. They used deep residual networks to classify the melanoma lesions and tested it on the data sets, ISBI, MED-NODE, and PH2. Their methodology showed the possibilities of deep residual networks to improve melanoma detection, as the best performance of deep residual networks was 98.5% on the PH2 dataset. The other salient technique was also lifted by [23] who applied the SVM as the classification technique and CNN as the feature learning technique. They could classify the skin cancer into four categories with a rate of 94.2% with reference to 3,753 images [24]. The experiment explains the effectiveness of combining the feature extraction capabilities of CNN and the classifying capabilities. Moreover, the question of the extent to which various types of classifiers, such as K-Nearest Neighbors (KNN), can be generalized to various situations has also been considered by people, as discussed further below. The author has suggested a segmentation of skin lesions lesion classification of melanoma by use of dermoscopy images. They have used the fuzzy pixel classification technique, then histogram thresholding to enhance the accuracy of segmentation [25]. The article mentions the recent research based on handcrafted feature extraction techniques. Wavelet transformation has been employed by Elgamel and Mahmoud [26] in the extraction of features, dimensionality reduction and thereafter the process of classification. They used k-nearest neighbor (k-NN) and artificial neural network (ANN) classifiers to determine skin cancer using clinical findings, and they correlated certain features that they observed in the dermoscopic images with the depth of tumors. In total, 81 features were acquired, which concentrated on such parameters as color, texture, shape, and pigment network. Both the logistic regression and the neural networks were used to classify and the overall accuracy was 80% [27].

### III. PROPOSED METHODOLOGY

The suggested methodology aims to apply Convolutional Neural Networks (CNN) to detect skin cancer through the utilization of the HAM10000 dataset to predict various skin lesion types [28]. The research adopts a formal approach, integrating data preprocessing, training, and testing with an ensemble learning method to enhance performance.

#### A- Data Collection and Preprocessing

The HAM10000 dataset is shown to be trained in Figure 2 and consists of seven different types of skin lesions [27]. The

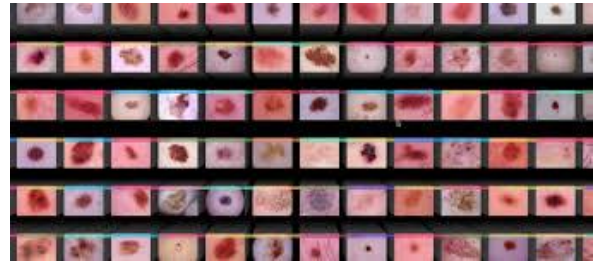


Fig. 2: HAM10000 Dataset [29]

images are downsized to 224 x 224 pixels to make them uniform and go through several preprocessing steps, such as data augmentation procedures, such as rotations, flipping, zooming, and shearing, to make the dataset diverse. This process prevents overfitting by recreating variability that exists in images of lesions in the real world situations.

The essence of the suggested system would be rooted in a CNN model which aims to automatically obtain hierarchical features of dermoscopic images. The CNN has the following structure:

#### B- CNN Architecture

The architecture of the proposed model is shown in Figure 3.

1. Input Layer: It takes the 150, 150, 3 preprocessed images.
2. Convolutional Layers: Convolutional layers enhance the input images by using filters to extract important features such as edges, shapes and textures [30].
3. Pooling Layers: Max pooling is used to downsampling the spatial dimensions of the image representation and preserve significant features.
4. Fully Connected Layer: Once the convolutional and pooling layers are done, the data is flattened and sent through a fully connected layer to categorize the extracted features [31].
5. Output Layer: Softmax activation is used to provide a probability of each skin lesion class.
6. Batch normalization (BN): BN accelerates the training process and stabilizes the learning process by standardizing the inputs of each layer [32].

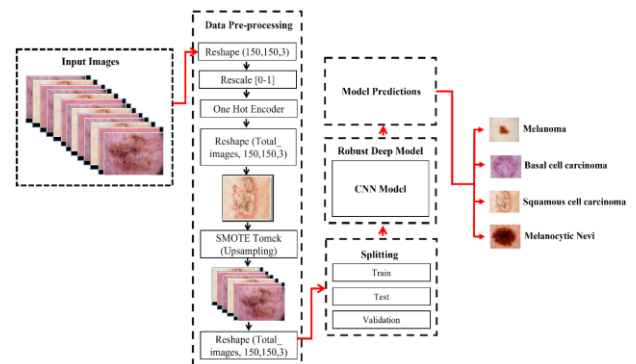


Fig 3: Ensemble Approach

7. Global Average Pooling (GAP): GAP layers are used to reduce overfitting and reduce the number of parameters, instead of using traditional fully connected layers.

Early Stopping and Dropout: Early stopping is used when training on the validation set has plateaued, with regularization methods such as dropout applied to further mitigate overfitting.

#### IV. RESULTS

The measures of accuracy is 97% is shown in Figure 4. Precision, recall, and F1 score are used to assess the CNN model's performance, as shown in Table 1. To make sure the model generalizes well across various dataset subsets, cross-validation is employed. The contribution of the ensemble method to the overall performance is also assessed.

#### VI. CONCLUSION

This research was aimed at exploring and implementing state-of-the-art machine learning techniques to identify skin cancer, both Convolutional Neural Networks (CNNs) and ensemble learning. Skin cancer, especially melanoma, is a severe health issue with its mortality rate increasing all over the world. Patient outcomes need to be improved through the early and accurate diagnosis, and the use of artificial intelligence (AI) in the diagnostic process is a possible solution to this problem. We employed the HAM10000 data set with pictures of seven different types of skin lesions to develop a deep learning model that will be able to discriminate between benign and malignant skin disorders. Some of the CNN architectures employed and their effectiveness evaluated include ResNet50, VGG16 and DenseNet. The capability of ResNet50 architecture to detect complicated patterns in dermoscopic images helped the architecture to show the best single accuracy of 84 percent of the models. An ensemble strategy that used the advantages of ResNet50, VGG16, and DenseNet was used to improve performance even more. This ensemble model with an accuracy of 95.78% was impressive. Additionally, to improve the detection system's resilience, model optimization strategies such as data augmentation and hyperparameter tuning were used. The high accuracy of the model (94.56%)

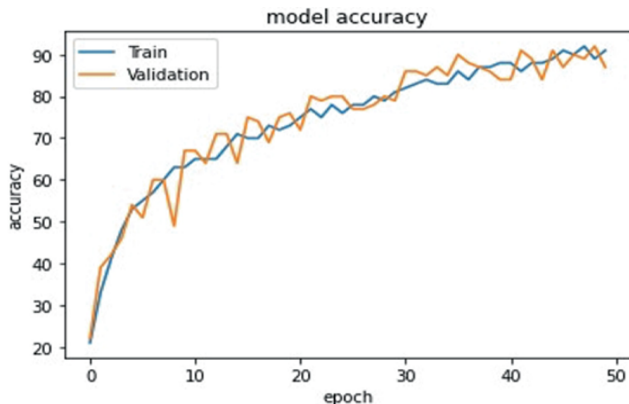


Fig. 4 Accuracy of the Proposed Model

TABLE I: PERFORMANCE OF THE PROPOSED MODEL

Metrics	Values%
Accuracy	95.78
F1 Score	94.56
Precision	95.12
Recall	94.80

, its high F1 score (94.56), its high precision (95.12), and high recall (94.80) all point to the fact that it can be considered reliable and that it may be used in clinical practice. It was advantageous since the ensemble learning method employed the strengths of all the models thereby enhancing the ability to detect all types of skin lesions and minimize false positives and false negatives. This work adds to the automated diagnostic systems that can help dermatologists with the detection of skin cancer at its early stages and potentially save lives by applying deep learning architectures. There are however some disadvantages of this research. Although the HAM10000 dataset is a large set of dermoscopic images, bigger and more diverse datasets might be future research to enhance the generalizability of the model. Further performance enhancement can also be through investigating the implementation of more machine learning models in addition to CNNs in an ensemble form such as Support Vector Machines (SVM) and K-Nearest Neighbors (KNN). This article illustrates the possibility of CNNs and ensemble learning methods in detecting skin cancer with the utmost accuracy. AI-driven diagnostic technologies may prove to be extremely helpful in helping medical professionals diagnose skin cancer more quickly and accurately with additional development and testing. This might improve patient outcomes and lessen the strain on healthcare systems.

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