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Skin Cancer Detection Using DCNN

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ABSTRACT

Skin cancer is the widest form of cancer. It is caused by un-repaired deoxyribonucleic acid (DNA) in skin cells, which generate genetic defects or mutations on the skin. Skin cancer tends to gradually spread over other body parts, so it is more curable in initial stages, which is why it is best detected at early stages. The increasing rate of skin cancer cases, high mortality rate, and expensive medical treatment require that its symptoms be diagnosed early. Considering the seriousness of these issues, researchers have developed various early detection techniques for skin cancer. Lesion parameters such as symmetry, color, size, shape, etc. are used to detect skin cancer and to distinguish benign skin cancer from melanoma. This paper presents a detailed systematic review of deep learning techniques for the early detection of skin cancer.

INTRODUCTION

Although melanoma is one of the most lethal types of skin cancer, a fast diagnosis can lead to a very high chance of survival. The combination of visual inspection and dermatoscopic images ultimately results in an absolute melanoma detection accuracy of 75%-84% by dermatologists. High performance can be achieved using deep neural networks at the expense of making the CNN wider, deeper, and more detailed, which forces the architecture to have extra parameters and requires a lot of computational resources for training and testing. Due to its compound scaling property, Efficient Net architecture can be thought of as an effective model to address these issues and improve the accuracy of skin cancer classification. However, because ML algorithms require hand-crafted features and because dermoscopic images have significant intra-class and minimal inter-class variability, it is exceedingly difficult to attain excellent diagnostic performance. Convolutional neural networks (CNNs)-based methods have received a lot of attention in recent years from researchers due to the huge improvement in prediction accuracy they offer. Due to its autonomous feature engineering and self-learning capabilities, Deep Learning (DL) based algorithms are being heavily studied for the categorization of skin cancer. High performance can be achieved using deep neural networks at the expense of making the CNN wider, deeper, and more detailed, which forces the architecture to have extra parameters and requires a lot of computational resources for training and testing. Efficient Net, one of the most flexible CNN architectures, can be used to attain high accuracy by utilizing the compound scaling method

LITERATURE SURVEY

Mehwish Dildar, Shumaila Akram, Deep Learning Techniques for Skin Cancer Detection [1]: Proposed deep neural networks play a significant role in skin cancer detection. They consist of a set of interconnected nodes. Their structure is similar to the human brain in terms of neuronal interconnectedness. Their nodes work cooperatively to solve particular problems. Neural networks are trained for certain tasks subsequently, the networks work as experts in the domains in which they were trained. In our study, neural networks were trained to classify images and to distinguish between various types of skin cancer. Different types of skin lesion from International Skin Imaging Collaboration (ISIC) dataset are presented. There are different techniques, such as ANN, CNN, KNN, and GAN for skin cancer detection systems. The mathematical accuracy of deep learning is 83.2%.

A. Murugan, Dr. S. Anu H Nair, Machine Learning Techniques for Skin Cancer Detection [2]: Skin disease is a common one in human diseases. In computer vision application, the skin color is the powerful indication for this disease. The proposed system identifies the skin cancer disease based on the images of skin. Initially, the skin is filtered using median filter and segmented using Mean shift segmentation. Segmented images are fed as input to feature extraction. GLCM, Moment Invariants and GLRLM features are extracted in this research work. The extracted features are classified by using classification techniques like Support vector machine, Probabilistic Neural

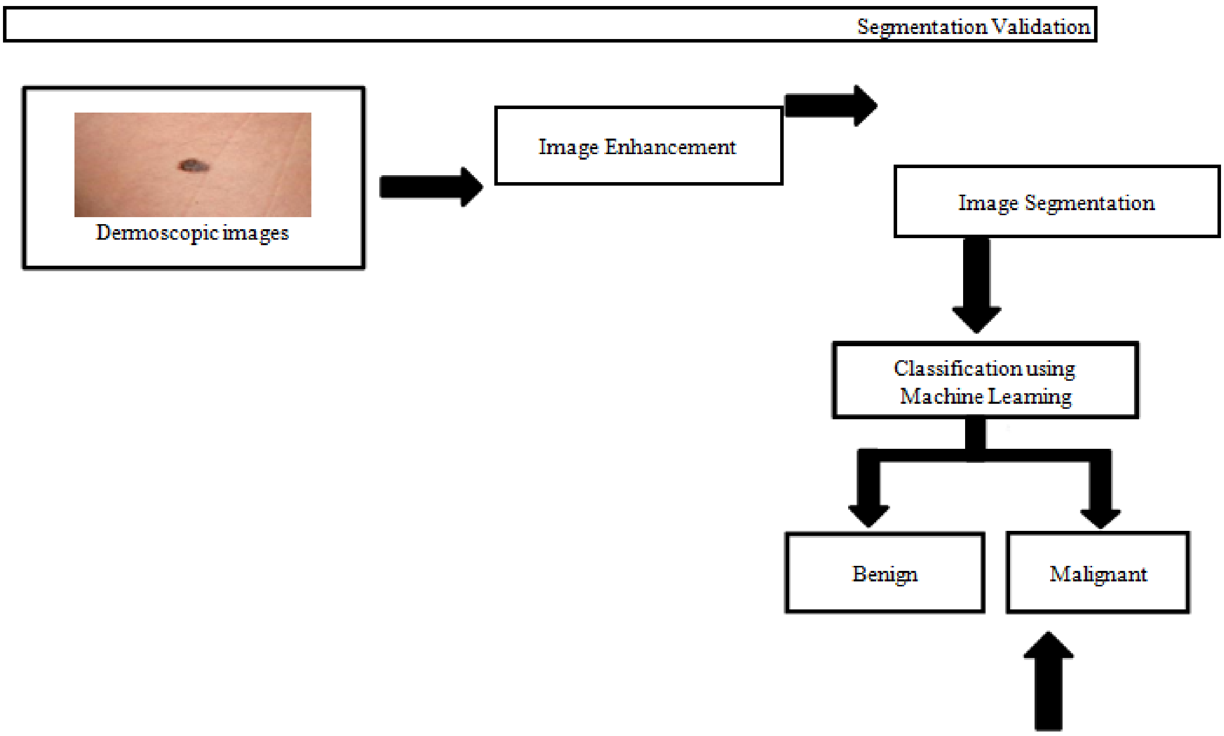
Networks and Random forest and Combined SVM+ RF classifiers. Here combined SVM+RF classifier provided better results than other classifiers. The mathematical accuracy of machine learning is 90%.

Shivangi Jain, Vandana Jagtap, Skin Cancer Detection using Image Processing [3]: The proposed system detecting the presence of cancerous cells in an image. It is implemented by using GLCM and SVM. In order to extract features from an image for classification GLCM is used. The Picture of the affected area is taken using camera and sent to Raspberry pi for pre-processing. The pre-processing is to reduces unwanted distortions and to enhance some image features. Image preprocessing involves three main methods. They are gray scale conversion, Noise removal and Image enhancement. Later the Segmentation is done in order to remove the region of interest from given image. Later the Feature extraction plays an important role in extracting information present in given image. To classify cancerous image from other skin diseases the classifier is used. The accuracy of mathematical analysis is 92.88 %.

Mehwish Dildar, Soumaila Akram, Muhammed Irfan, Hikmat Ullah Khan, Artificial Neural Network (ANN)-Based Skin Cancer Detection Techniques [4]: The proposed system using an artificial neural network is a nonlinear and statistical prediction method. Its structure is borrowed from the biological structure of the human brain. An ANN consists of three layers of neurons. The first layer is known as the input layer; these input neurons transfer data to the second/intermediate layer of neurons. The intermediate layers are referred to as hidden layers. In a typical ANN, there can be several hidden layers. Intermediate neurons send data to the third layer of output neurons. Computations are learned at each layer using backpropagation, which is used for learning the complex associations/relationships between input and output layers. It is similar to a neural network. Currently, in computer science, the term neural network and artificial neural network are used interchangeably. The accuracy of mathematical analysis is 91%.

Jaisakthi S, Mirunalini, Chandra Bose Aravindan, Rajagopal Appavu, Classification of skin cancer from dermoscopic images using deep neural network architectures [5]: Images are a crucial component of skin cancer prognosis. Despite the fine-grained variations in its appearance, cancer can be identified from dermoscopic pictures. automatically and accurately distinguish between melanoma and non-melanoma skin cancer kinds. Here, a transfer learning architecture called EfficientNet was employed. This design automatically scales the depth, breadth, and resolution of the network as it learns more intricate and fine-grained patterns from lesion photos. It also used metadata data to enhance the classification outcomes. Ranger optimizer is used to increase EfficientNet's efficiency since it significantly decreases the amount of hyper parameter tuning needed to attain state- of-the-art results showed that EfficientNet variants beat EfficientNet-B6 in the skin lesion categorization tests. Mathematical analysis has a 97% accuracy rate.

PROPOSED METHOD



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CONCLUSION

This research intends to advance skin lesion digital diagnostics and explore the usefulness of a new CNN architecture called Efficient Net. The automated technique for classifying skin lesions that makes use of patient meta data and dermoscopic pictures. It conducted multiple tests utilizing two distinct transfer learning strategies, such as feature extractor and fine tuning, to address these problems. The last layers of the pre-trained architecture were combined with a straightforward neural network that accepts contextual data as input to further enhance the findings. This approach reduced the issue of hyper-parameter tuning and produced a superior AUC score of 0.9681 for Efficient B6 with Ranger Optimizer It is also compared results with the existing work and obtained a better score.

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