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Skin Melanoma Cancer Detection Using Particle Swarm Optimization Algorithm and Deep Learning

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ABSTRACT

Skin cancer is one of the most prevalent and life-threatening forms of cancer, with its incidence rapidly increasing over the past few decades. Early detection plays a crucial role in improving the survival rate of individuals diagnosed with skin cancer, particularly melanoma, which is the deadliest form. Traditionally, skin cancer diagnosis has relied on time-consuming and invasive methods such as skin biopsy. However, with advancements in technology, automated diagnosis through intelligent techniques has shown the potential to expedite the detection process and increase diagnostic accuracy. Among the various methods explored for skin cancer detection, Convolutional Neural Networks (CNNs) have emerged as one of the most effective deep learning models. CNNs are capable of learning and extracting intricate features from skin images, making them highly suitable for melanoma classification tasks. In this study, a deep CNN model is designed and evaluated for classifying melanoma from other skin lesions. Key parameters of the CNN, such as filter size and the number of filters, are optimized using the Particle Swarm Optimization (PSO) algorithm. This optimization process aims to minimize classification errors and enhance the overall performance of the model. The simulation results reveal that the proposed method outperforms existing frameworks, achieving a remarkable accuracy rate of 96% on the utilized dataset, demonstrating the effectiveness and reliability of the proposed approach for melanoma detection.

1. INTRODUCTION

Melanoma is a type of skin cancer in humans caused by abnormal cells. If not diagnosed in time, these cells can spread to other parts of the body and lead to death [1-3]. There are three main types of skin cancer: 1) Squamous Cell Carcinoma (SCC), 2) Basal Cell Carcinoma (BCC), and 3) Melanocyte-derived melanoma. The first two types are classified as non-melanoma skin cancers. Basal cell carcinoma grows slowly and is more common among

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individuals with fair skin. While not fatal, delayed diagnosis of this type can result in skin lesions, especially on the face. Treatment involves removing the lesion along with surrounding tissue [4-7].

Squamous cell carcinoma typically manifests as a hard mass with a scaly surface and may cause ulceration. Melanoma, on the other hand, is aggressive and, if not diagnosed promptly, can result in fatal outcomes. Since melanoma often resembles other skin lesions (e.g., moles, benign tumors) in terms of color, shape, and size, it poses diagnostic challenges for physicians. Therefore, various methods have been developed to distinguish melanoma from other skin lesions [8-10].

Dermoscopy is a non-invasive imaging technique widely used for analyzing skin lesions based on their morphological characteristics. By eliminating surface reflections, dermoscopy enhances the visual representation of deeper skin layers, thus providing detailed insights into skin lesions. One of the critical applications of dermoscopy is the early detection of melanoma a melanocytic lesion that can sometimes appear non-melanocytic. However, reviewing dermoscopic images by dermatologists is often time-consuming and prone to errors (even trained specialists may produce significantly varying diagnostic results). Consequently, automated diagnostic approaches are in high demand.

Classifying pigmented skin lesions using dermoscopy requires a two-step diagnostic process [2][3]. The first step involves distinguishing melanocytic lesions from non-melanocytic ones, while the second step entails differentiating melanoma from benign melanocytic lesions. This study aims to detect melanoma in dermoscopic images through image processing techniques.

2. EXISTING METHODS

Skin cancer is a significant public health issue in the United States, with more than 5 million new cases diagnosed annually. Melanoma, the deadliest type of skin cancer, accounts for 75% of skin cancer-related deaths. In 2015, the global incidence of melanoma was estimated at over 350,000 cases, with nearly 60,000 deaths. However, if diagnosed early, the survival rate exceeds 95%.

In [1], the goal is to ensure that the features used in deep learning methods align with clinically meaningful characteristics for diagnosing skin lesions. Specifically, a precise deep learning model is trained to classify each dermoscopic image by predicting the probability score for each class. Subsequently, the significance of the features is analyzed.

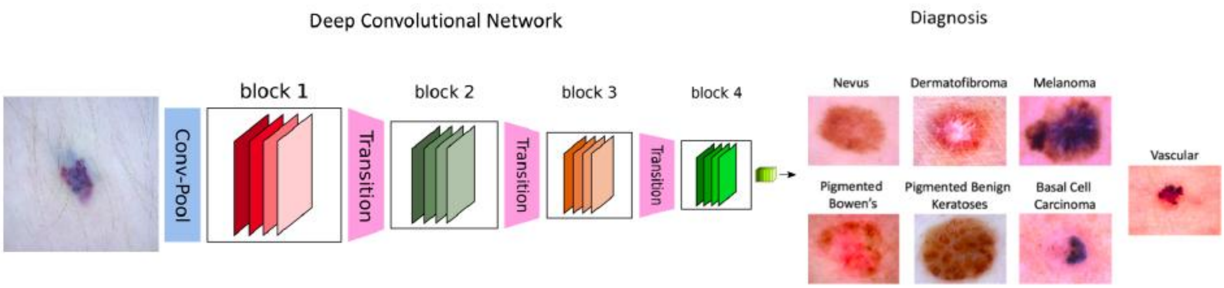


Fig. 1. Method presented in [1]

In [2], various types of skin lesions, such as basal cell carcinoma, benign keratosis, dermatofibroma, vascular lesions, melanoma, and melanocytic nevi, are classified with an accuracy exceeding 80% using the VGG-16 model. The sparse coding algorithm eliminates the need for large annotated datasets to learn appropriate features. Data augmentation was applied to the dataset, and with the integration of sparse coding and convolutional neural networks, high accuracy was achieved. The PH2 dataset, which contains labeled images (1,600 melanoma images versus 1,600 non-melanoma images), was used in this study.

In [3], convolutional neural network (CNN)-based methods are proposed to improve lesion segmentation performance. The proposed ensemble technique includes VGG19-UNet and DeeplabV3. Extensive experiments were conducted on the ISIC 2018 dataset to demonstrate the efficacy of the proposed model. The dataset contains

2,594 dermoscopic images and was randomly split into 80% for training and 20% for validation. The proposed model achieved an overall accuracy of 93.6%.

Some sample images for lesion segmentation from the training dataset are shown in Figure 2, where blue lines represent the segmentation boundaries.

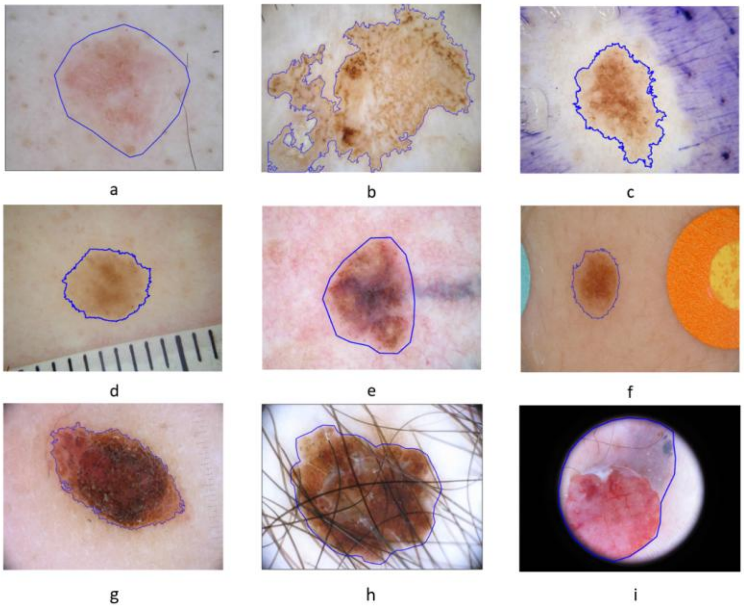


Fig. 2. Images for skin lesion segmentation from [3]

Early detection and classification of skin cancer significantly improve the chances of successful treatment. In recent years, convolutional neural networks (CNNs) have emerged as a powerful tool to assist in skin cancer diagnosis. In [4], the HAM dataset was utilized to demonstrate a strategy for classifying skin cancer. VGG16, VGG19, and a proposed deep CNN were implemented, trained, and evaluated. The network parameters and the training process were detailed. The dataset was split into 80% for training and the remainder for testing, with 20% of the training data reserved for validation during training. The performance of all three networks was compared in terms of average accuracy and overall loss.

Most automated skin cancer detection methods developed to date have focused only on malignant melanocytic melanoma. Non-melanocytic malignant skin lesions have not been thoroughly studied due to the lack of datasets with diverse lesion classes. In [5], the automatic detection of malignant skin lesions is investigated. A two-step diagnostic approach, inspired by dermatologists, is followed. Using a deep learning model, skin lesions are first classified as melanocytic or non-melanocytic, and then malignant types are identified using other deep learning models. Performance evaluations indicate that melanocytic and non-melanocytic skin lesions are detected with the highest accuracy. The results also show that malignant melanocytic lesions can be classified with greater accuracy than non-melanocytic malignant lesions.

The recent development of deep learning algorithms, such as CNNs, has enabled image classification without the need for manual image segmentation and feature engineering, while achieving high performance with sufficient training data. Therefore, in [6], a deep convolutional neural network is proposed to classify melanoma images into benign and malignant categories. The proposed network architecture consists of multiple sets of convolutional layers and max-pooling layers, followed by a dropout layer and a fully connected layer. Based on simulation results on 352 test images, the proposed network achieves accuracy, sensitivity, and specificity of 84.76%, 91.97%, and 78.71%, respectively. With the model's strong performance, there is hope that it can be developed for real-world applications to assist specialists in better diagnosis and treatment.

3. PROPOSED METHOD

CNNs are a type of deep learning model used for processing data and images [11-13]. CNNs are built upon a mathematical structure consisting of at least three types of layers: convolutional, pooling, and fully connected layers. The convolutional and pooling layers perform feature extraction, while the fully connected layer sends the extracted features to the final output for classification. The convolutional layer plays a critical role in CNNs, as described below.

3.1. Convolutional Layer

Convolution is a specific type of linear operation used for feature extraction. This layer performs dot products between two matrices. The convolution process involves applying a small matrix, known as a filter or kernel, over an input image to extract essential features. The filter moves across the image, performing element-wise multiplication at each position and summing the results. This process produces convolutional features that are then passed to the next layer for further processing.

The first convolutional layer identifies basic features such as edges, corners, and other simple shapes. As the image passes through subsequent layers, the network becomes capable of recognizing more complex features by building upon the information gathered from earlier layers. Thus, deeper layers in the network can identify increasingly sophisticated features, such as objects and faces.

3.2. Pooling Layer

The pooling layer reduces the dimensions of feature maps through a sampling operation. There are two types of pooling:

1. Max Pooling
2. Average Pooling

The primary purpose of a pooling layer is to reduce the number of parameters in the input tensor, which has the following benefits:

- Helps mitigate the problem of overfitting.
- Extracts representative features from the input tensor.
- Reduces computational costs, thereby improving efficiency.

3.3. Fully Connected Layer

The fully connected layer belongs to the category of feedforward neural networks. These layers form the final few layers of the network. The input to a fully connected layer is the output from the last pooling or convolutional layer, which is flattened into a one-dimensional matrix and then passed to the fully connected layer. In this layer, each input is connected to every output through learnable weights.

3.4. Flowchart of the Proposed Method

Figure 3 illustrates the final flowchart of the proposed segmentation method. The segmentation technique is based on the k-means clustering algorithm, but determining its centroids is challenging. To address this, the centroids are selected using the Particle Swarm Optimization (PSO) algorithm. The PSO algorithm optimizes this process to enhance segmentation accuracy, which is critical for extracting tumor regions in the images.

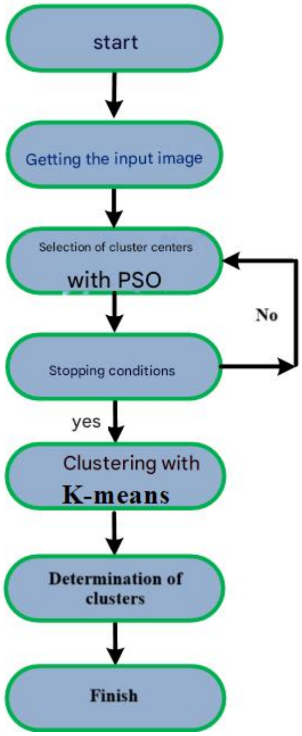


Fig. 3. Flowchart of the proposed method for clustering

Finally, the flowchart of the proposed classification method is illustrated in Figure 4. The method comprises the following main steps:

1. **Network Architecture Definition**: The architecture of the convolutional neural network (CNN) is first defined. The network includes the following layers: imageInputLayer, convolution2dLayer, batchNormalizationLayer, reluLayer, maxPooling2dLayer, fullyConnectedLayer, softmaxLayer, and classificationLayer.
2. **Design Variable Configuration**: The convolution2dLayer configuration is dependent on key design variables, namely filterSize and numFilters. In the proposed approach, these parameters are optimized to minimize classification error.
3. **PSO Optimization**: The values for filterSize and numFilters are obtained using the Particle Swarm Optimization (PSO) algorithm.
4. **Error Evaluation**: The PSO algorithm evaluates the classification error associated with each candidate solution.
5. **Stopping Criterion Assessment**: The algorithm checks whether the stopping condition is met. If not, new candidate solutions are generated using the Cuckoo Search algorithm.
6. **Solution Deployment**: Finally, the best solutions obtained are used to configure the CNN for classification.

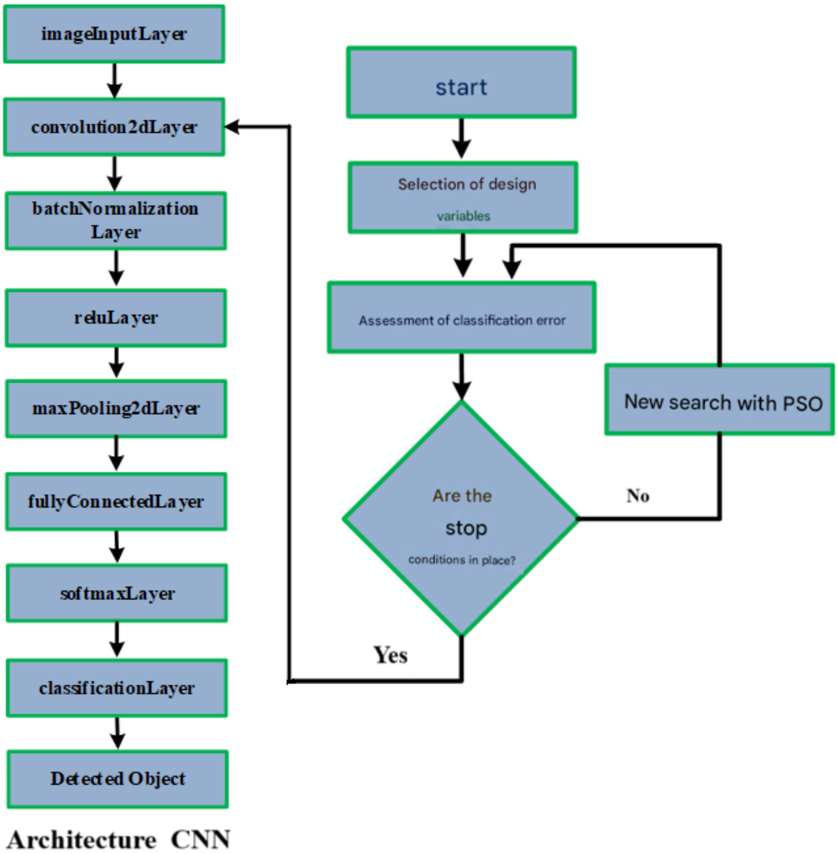
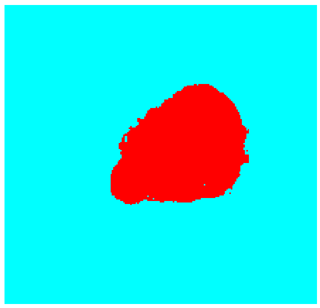


Fig. 4. Flowchart of the proposed method for classification.

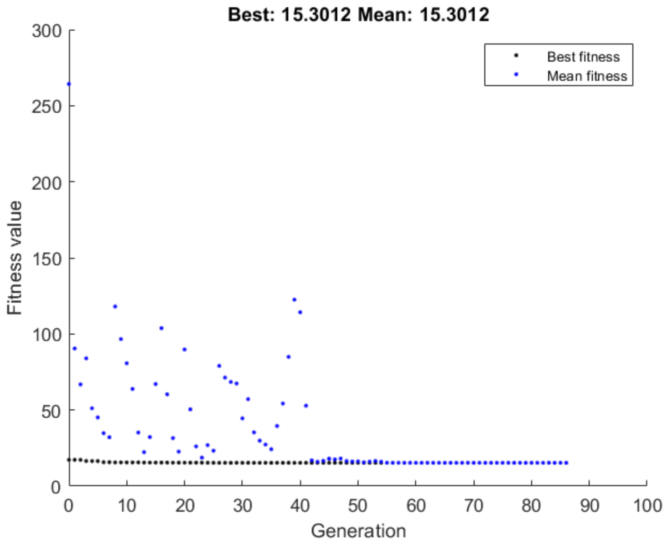
4. SIMULATION RESULTS

The proposed algorithm and existing methods were implemented using MATLAB software from MathWorks. The processor used is an Intel(R) Core™ i5-4460 CPU @ 3.2 GHz with 16 GB of RAM. Below are the simulation results and a comparison of the results with existing methods. The combined k-means and PSO algorithm was applied to a sample image (Figure 5). Here, the results for two clusters are shown. The optimization process obtained from the PSO algorithm is also displayed.

(a)



(b)



(c)

Fig. 5. a) Sample image, b) Clustering performed, c) Optimization process.

In this research, accuracy and precision metrics are used to evaluate the performance of the proposed method and compare it with existing methods. The PH2 database contains 200 images, divided into three disease groups: 80 benign tumors, 80 atypical moles, and 40 melanomas. The accuracy of the proposed algorithm on the used dataset is 96%, indicating its high performance. The accuracy chart related to the algorithms used in this research is shown in Figure 6. A key advantage of the proposed method over existing methods is the optimal selection of centers by PSO. In the proposed method, the parameters are selected by the PSO algorithm in such a way that the accuracy of the results is increased. The precision chart of the proposed method and existing methods is plotted in Figure 7.

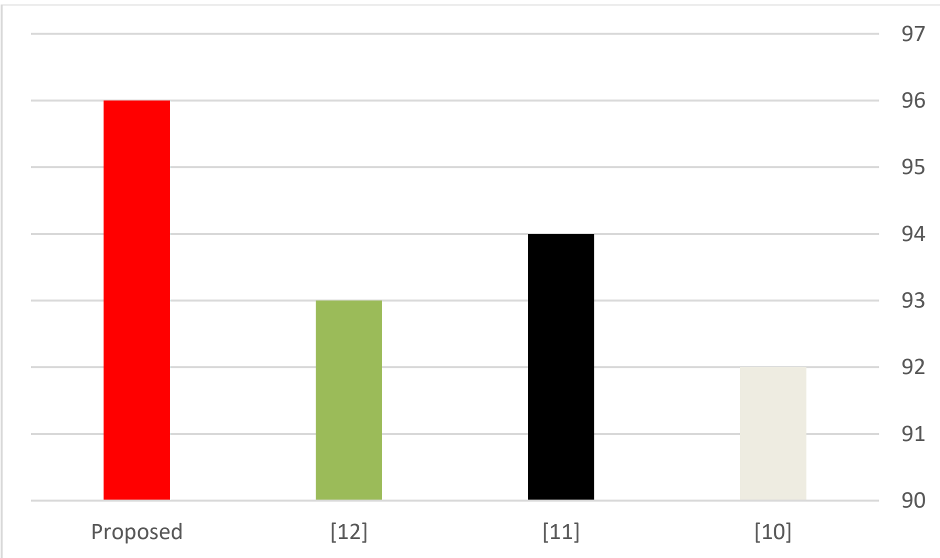


Fig. 6. Performance evaluation of the proposed method and comparison with existing methods based on accuracy.

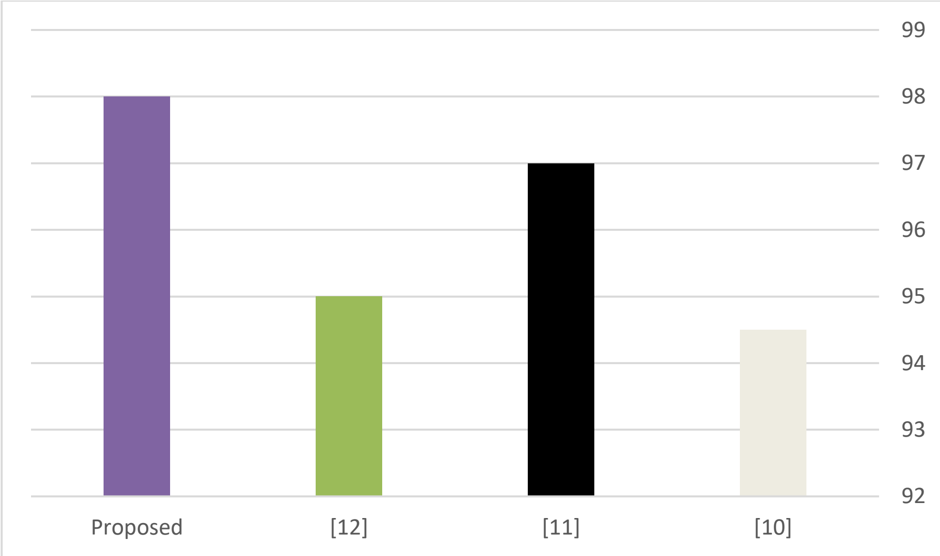


Fig. 7. Performance evaluation of the proposed method and comparison with existing methods based on accuracy.

5. CONCLUSION

Early detection of melanoma can prevent the patient's death, and early detection of other lesions helps in faster treatment. In basal cell carcinoma, late detection causes the lesion to spread in the face. The goal of this research was to achieve earlier detection of skin melanoma and to differentiate between non-invasive skin lesions and melanoma, so that appropriate treatment can begin at the right time for each type. In the proposed method, segmentation is performed by combining the PSO algorithm and k-means. Then, classification is done using deep learning. The proposed method was applied to a number of standard images. The simulation results show the high performance of the proposed method compared to existing methods.

Declaration

We acknowledge that we used ChatGPT to enhance the academic writing of our manuscript while ensuring the originality and integrity of our work.

Transparency Statement

The data supporting this study are available upon reasonable request to the corresponding author, subject to ethical and confidentiality considerations.

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Declaration of Interest

The authors declare that they have no competing interests.

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