A novel Artificial Intelligence-based Diagnosis of Skin Melanoma from Dermoscopic Images

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Abstract

Malignant melanoma, which is another name for melanoma, is distinguished by variations in skin tones brought on by aberrant pigment-producing cell activity. The aim of this work is to raise the accuracy of melanoma diagnosis using dermoscopic images by employing Artificial Intelligence (AI). Pre-processing, segmentation, feature extraction, and classification are the four major phases of the predicted skin cancer detection model. Image enhancement and hair removal also seem to be part of the primary pre-processing phase of dermoscopic images. To reduce the noise in dermoscopic images, Gaussian filter is used. The K-means algorithm Clustering is the segmentation process used in this research. Regarding pre-processing, an efficient region-growing algorithm coordinates lesion segmentation. Ant Colony Optimization (ACO) is used in feature extraction. During colour morphology, morphological transformation, local features are all mined during the stage of feature extraction. Furthermore, in the classification phase, novel AI-based method is used. In order to reduce process complexity, the features are exposed to a new adapted form of the ant colony optimization process. As a consequence, the procedure is more precise and reliable. To evaluate the effectiveness of the recommended approach, the proposed method is contrasted with the existing methods.

Keywords: Dermoscopic images, Convolutional Neural Network, Ant Colony Optimization, Gaussian filter

1. Introduction

One of the most common causes of mortality these days are cancer. Melanoma is another name for skin cancer since it has a malignant trait. The number of people whose death from cancer are expected to rise daily. Skin cancer is one of the cancers with the highest patient population [1]. It occurs because skin cells proliferate quickly, which can occasionally lead to skin cancers. Skin cancer from melanoma has been a leading cause of mortality. Melanocytic cells can be found in human tissue. Therefore, malignant melanoma is caused by the fast proliferation of aberrant melanocytic cells. Melanoma typically manifests as a fresh dark spot on the skin or as an expansion of an existing mole[2]. After that, it penetrates the skin deeply and eventually reaches the blood vessels. Later, it will impact other organs and migrate toward other areas of the body. Numerous factors, including prolonged exposure to UV light, contribute to the cells rapid development. The three primary kinds of skin cancer are basal cell carcinoma (BCC), melanoma cell carcinoma (MCC), and squamous cell carcinoma (SCC). BCCs occur when lesions in skin cells known as basal cells expand fast. Melanoma develops in melanocyte skin cells whereas SCC damages squamous skin cells. Considering that it involves the entire body, it is the most deadly type of skin cancer. Patients with melanoma who are diagnosed early enough may make a full recovery.

Dermatologists have a difficult and crucial challenge when trying to make an early diagnosis of melanoma since several other skin lesions may resemble it physically. Dermoscopy is a method that uses a microscope and specialised lighting to view the inner layers of skin [3]. It is thought to be the most extensively utilised method for in-person inspection of skin lesions with pigmentation. Dermoscopic pictures offer a lot of potential for early malignant melanoma identification. Dermoscopy is a branch of healthcare that has made significant advances due to the introduction of mechanised tools, computer-aided technology, and amplification lenses. With the utilization of image processing algorithms with parameters for the size of the affected region, colour, border, and asymmetry, computer assisted technologies enable dermatologists to identify skin cancer more effectively.

The conventional approach of skin cancer detection is intrusive, uncomfortable, and time-consuming. Therefore, computer-aided diagnostics is utilised to identify skin cancer in order to resolve the above mentioned problems. There is no direct touch with the body because this technology demands a skin image [4]. This technique is non-invasive and will lessen discomfort. The clinical assessment of skin lesions has been made easier with the use of a number of computer-aided diagnostic systems for digital dermoscopic pictures. Artificial Intelligence is now the subject of advanced study and has a wide variety of applications. Therefore, Artificial Intelligence is utilised more rapidly and effectively to identify malignant cells since it may improve the identification of risky cells straightforward, particularly when convolutional neural networks is utilized. Artificial Intelligence is efficient and capable of handling a lot of data, including limitless data. To get rid of the picture highlights, deep learning algorithms are applied. Neural networks, a manifestation of artificial intelligence technology, have also shown outstanding outcomes in the detection of melanoma.

The created framework's major contribution is summed up as follows:

- ❖ Initially, the framework collects and processes Dermoscopic images.
- ❖ Additionally, a Gaussian filter is used to remove extra noise from the dermoscopic images.
- ❖ The K-means Clustering Algorithm is the segmentation technique used in this study.
- ❖ Feature extraction carried out by Ant Colony Optimization (ACO).
- ❖ The ACO-CNN perceives the highlighted region in dataset and categorizes skin cancer as benign or normal.
- ❖ The inferred method's success is acknowledged and compared to other strategies to demonstrate its potency.

The rest of this essay is structured as follows: Section 2 presents some of the literature reviews and provides the examination of them. In Section 3, the suggested ACO-CNN architectures are thoroughly examined. The experiment's results are provided and discussed in section 4, and a full evaluation of the recommended technique in context of existing best practises is done. The last section of the paper is Section 5.

2. Related works

For the purpose of detecting skin cancer, Rasmiranjan Mohakud and Rajashree Dash [5]used a hyper-parameterized convolutional neural network classifier based on grey wolf optimization. In order to optimize the hyper parameters of Convolutional Neural Network, the technique used a suitable encoding scheme and used a Grey Wolf Optimization algorithm. Evaluating the model's performance to that of genetic algorithm-based hyper-parameter optimization and particle swarm optimization demonstrates the model's efficacy. CNN used the multiclass data set for skin lesions from the International Skin Imaging Collaboration. The experimental findings unambiguously show that the suggested model outperforms previous known models in a competitive manner. By employing appropriate optimization methods, such as the hybrid Salp Swarm Algorithm, Grasshopper optimization algorithm, and Arithmetic Optimization Algorithm, the performance of the model may be improved.

Jun Li et al. [6]proposed dual meta-learning framework to segment the pancreatic cancer. The performance of segmentation is limited by the low and undetectable borders, which is made worse for deep learning approaches with fewer training samples by the higher threshold of images capture and annotation. Researchers gather pancreatic cancer idle multi-parametric MRIs from various researches to build a relatively large dataset for improving the Computed Tomography pancreatic cancer segmentation in order to address this problem brought on by the small-scale dataset. So, for pancreatic cancer, researchers suggest a deep learning segmentation method with a dual meta-learning framework. High-level characteristics become more discriminative as a result of its ability to combine salient information from Computerised Tomography pictures with the general understanding of tumours gained from idle MRIs. The randomised intermediate modalities between CT and MRI are initially created in order to seamlessly cover the gaps in outer appeal and provide rich intermediary representation for the subsequent meta-learning technique. Researchers then use model-agnostic meta-learning based on intermediary modalities to identify and transfer commonalities. The interference caused by internal differences is finally reduced by using a meta-optimizer to adaptively understand the relevant features inside CT data. The suggested approach is a potent pancreatic cancer segmentation framework that is simple to integrate into existing segmentation networks and has promise as a viable paradigm for addressing the problems of data scarcity with idle data.

The New Buzzard Optimization Algorithm is employed by Ali Arshaghi et al. to identify skin cancer in images using feature selection techniques [7]. This work presents a novel technique for classifying dermoscopy pictures into benign and malignant categories. In order to improve picture quality prior to developing the basic skin cancer detection system, pre-processing is used. The Otsu threshold approach is then used to separate the lesion region from the healthy parts. Using various optimization techniques, nine form features and nine colour characteristics are recovered from the segmented picture. SVM, KNN, and Decision Tree algorithms were used to classify the data at the conclusion of the procedure. According to the findings, the accuracy of the SVM classifier when combined with the buzzard optimization approach for feature extraction is 94.3%. The outcome demonstrates the buzzard optimization algorithm's excellent feature extraction capabilities but it requires large number of datasets for the process.

3. Methodology

The Proposed method employed Ant Colony Optimization and Convolutional Neural Network. The method utilizes the ISIC 2016 dataset for the training and testing phases. After that, the dermoscopic images are pre-processed to remove unwanted noise using a Gaussian filter. Followed by the segmentation is carried out by employing K-mean Clustering algorithm. Furthermore the Ant colony optimization is used for the extracting the features from the dataset. Then the Classification is done by employing the convolutional neural network and its layers. The suggested framework is shown in Fig. 1.

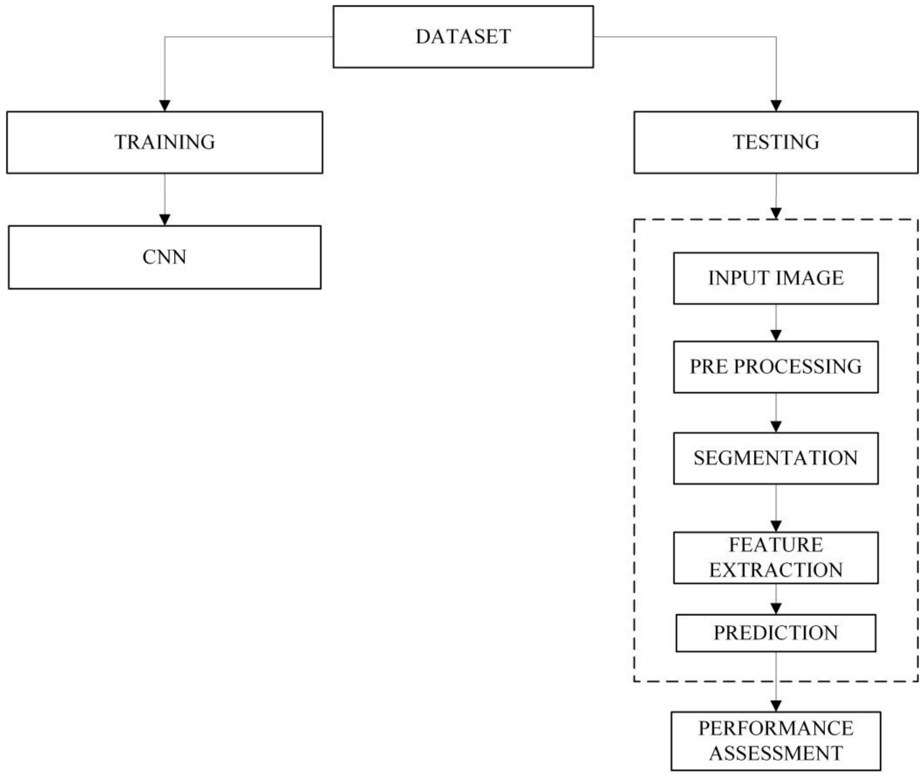

Figure.1: Proposed Framework

3.1 Dataset Collection

The ISIC 2016 [8]. Dermoscopic datasets is used in this paper. It includes 900 samples, containing 727 BEN (Benign) and 173 MEL (Melanoma) samples. 70% and 30% of the samples in the datasets are utilized for testing and training process respectively. To provide the network enough training, the samples in the training set was kept higher. Subsequently, the performance of the system was evaluated to use the test data.

Table 1: **Collected dataset**

Classes	Training samples	Testing samples	Total samples
MEL	95	78	173
BEN	546	181	727
TOTAL	641	259	900

3.2 Pre-processing

Pre-processing is the first step in the detection of skin melanoma cancer. It is used to fill the gaps in the datasets and erase the unnecessary data. Independent and anomalous noises affect the dermoscopic images which decrease the analysis rate of the sample images. The dermoscopic images are mostly affected by the speckle noises which are caused due to internal and external factors. Hence, to reduce the noises in dermoscopic images, the generated Gaussian filter is applied. The generated Gaussian filter is employed to decrease the noise in the representations and to reduce the derivatives of geographical intensity that remain in the representations. The Gaussian filter is applied to replace the noisy pixel in the representation with the average value of the neighbouring pixels which is based on Gaussian distribution. In order to diagnose melanoma skin cancer, the ACO-CNN model employs the noise-reduced images. The Gaussian function is given as

$$G(y) = \frac{1}{\sqrt{2\pi\sigma^2}} e^{\frac{y^2}{2\pi\sigma^2}} \tag{1}$$

Where σ is the standard deviation of the distribution. The distribution is assumed to have a mean of 0.

3.3 Segmentation

A classification method can perform better with effective skin picture segmentation. To segment the pre-processed image obtained from the previous section, a clustering method is utilized [9].K-means clustering, one of the most widely used techniques for colour-based segmentation. Each pixel in the image is initially assigned to one or even more clusters in order to minimize the total of the squares for each cluster, and then the group pixels are updated using the innovative means obtained for each group. Equation 3 is used to detect the cluster in the image.

$$\mathrm{A}_\mathrm{i}^{(\mathrm{t})} = \left\{\mathrm{R_p}: \left\|\mathrm{R_p} - \mathrm{s}_\mathrm{i}^{(\mathrm{t})}\right\|^2 \leq \left\|\mathrm{R_p} - \mathrm{s}_\mathrm{j}^{(\mathrm{t})}\right\|^2 \text{first all j },1 \ \leq \mathrm{j} \ \leq \mathrm{k}\right\} \tag{2}$$

Where, $A^{(t)} = cluster,\ R_p = Observation, s_i^{(t)} = initial\ means$

Where, $\mathrm{A^t} = \text{cluster}, \mathrm{s_j} = observation, R_i^{(t+1)} = updated\ mean$

The clusters are updated by determining the new mean using the following eqn. (4)

$$R_i^{(t+1)} = \frac{1}{\left|A_i^{(t)}\right|} \sum_{S_j \epsilon a_i^{(t)}} S_j \tag{3}$$

The K-means clustering algorithm generates an image with pixels organized into various clusters as its output. Intensity-based thresholding is performed by the clustered image to produce a binary image with lesion and some noise pixels. The binary images that were produced after applying an intensity-based cut off to colour images obtained using K-means clustering [9].

3.4 Feature Extraction

Ant Colony optimization algorithm

Nowadays, approximative optimization uses the ant colony optimization methodology. The search behaviour of the ants drives the optimization of the ant colony. Ants utilise their main means of communication to find the shortest path to their food supply. This ant's special quality is utilised by the Ant Colony Optimization approach (ACO). The characteristics in the dermoscopic pictures are extracted here using ACO to classify skin cancer as benign or malignant. One key aspect of the database that has to be modified initially is the pheromone rate. A matrix (h) with a size of G*G, where G is the number of distinct extracted features in its columns and rows has all the pertinent data necessary to explore the feature. After adjusting the ant colony optimization parameters, the primary computation, such as the empirical function F, is computed. Identify the resource and best-constrained subset for the following iteration.

The first and most important step in using the Ant Colony Optimization method is the initialization of its components. Many potential ants are present. The ACO algorithm also has strong robustness and an isolated calculative process. ACO works brilliantly when it comes to resolving complex optimization problems and is easily replaced with other strategies. ACO employs the updated pheromone, and ants move in the search area in accordance with mathematical calculations. The basis of ACO is local and international searches. Figure 2 shows the flowchart of the proposed framework.

Transition probability of region (m)

The specular highlight is determined by using the method for determining a region's transition probability.

$$Q_a(s) = \frac{s_a(s)}{\sum_{i=1}^{d} s_i(s)} \tag{4}$$

Here $s_a(s)$ reflects the total amount of pheromone in area A, whereas d is the number of ants worldwide.

The Equation for pheromone update

Pheromones, which are substances released by an ant, alter other ants behaviour. The pheromone update formula employed by ants for communication is,

$$p_j(p+1) = (1-s)p_j(p) \tag{5}$$

Here, "s" stands for the rate of pheromone evaporation.

Edge traversed equation

Every ant updates the neighbourhood pheromone after completing each stage of development. Only the newest recent edge that an ant has travelled uses it.

$$\Tau_{ij} = (1 - \Psi) \cdot \Tau_{ij} + \Psi \cdot \Tau_0 \tag{6}$$

3.5 Classification

3.5.1 Convolutional neural network (CNN)

The classifiers of Convolutional Neural Network (CNN) are used to recognise the lung tumour nodules. It efficiently assesses the CT representations and extracts the needed characteristics through its multi-layered construction. Convolutional Neural Network classifiers contain four layers: input image, fully connected layer, convolutional layer, Max pooling layer, and output. Before the training stage, the convolutional neural network ranges the intensity values of the representation pixel. During the training stage, CNN is the fastest model. The CT representation given as input should have the same size.

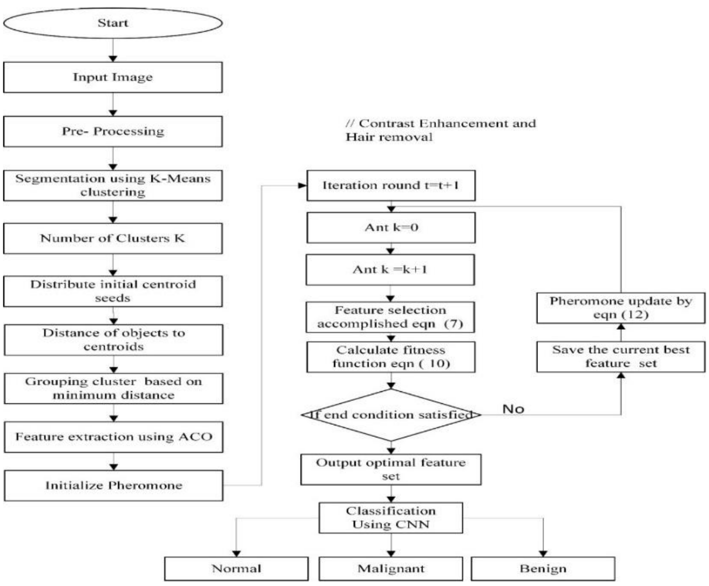

Figure 2: **Flowchart of the proposed framework**

4. Result and Discussions

The intended approach has been researched utilising datasets of dermoscopic images. The classification and detection of skin melanoma cancer from dermoscopic images is carried out using the Ant Colony Optimization-based CNN. Operating characteristics including Precision, Accuracy, F-measure, and Recall are utilized to evaluate the presentation of the proposed model.

Accuracy

The degree of similarity between a computation and its genuine value is known as accuracy. It is the proportion of accurately calculated data to all measurements. Accuracy is stated using the Eqn (13).

$$Accuracy = \frac{T_{Pos} + T_{Neg}}{T_{Pos} + T_{Neg} + F_{Pos} + F_{Neg}} \tag{7}$$

Precision

The level of precision or proximity between two or more calculations was called to as precision. Precision indicates how predictable a measurement is and relies on accuracy. Precision can be obtained from Eqn (14).

$$P = \frac{T_{Pos}}{T_{Pos} + F_{Pos}} \tag{8}$$

Recall

The portion of all appropriate results that have been effectively gathered by the algorithm is known to as recall. The ratio of true positives to false negatives and accurate positives is the term used to explain it. Recall may be estimated via Eqn (15).

$$R = \frac{T_{Pos}}{T_{Pos} + F_{Neg}} \tag{9}$$

F-1 Score

The F-1 Precision and recall are combined to determine a score. The F-1 score is strongly influenced by the precision and recall values. It is depicted in Eqn (16).

$$F1 - score = \frac{2 \times precision \times recall}{precision + recall} \tag{10}$$

Table 1: **Performance evaluation of the proposed ACOCNN**

Model	Accuracy	Precision	Recall	F-1 Score
DCNN	81.41%	88.23%	90.42%	82.59%
Res net-50	84.00%	86.60%	89.30%	87.90%
Proposed method	85.20%	87.30%	90.10%	88.50 %

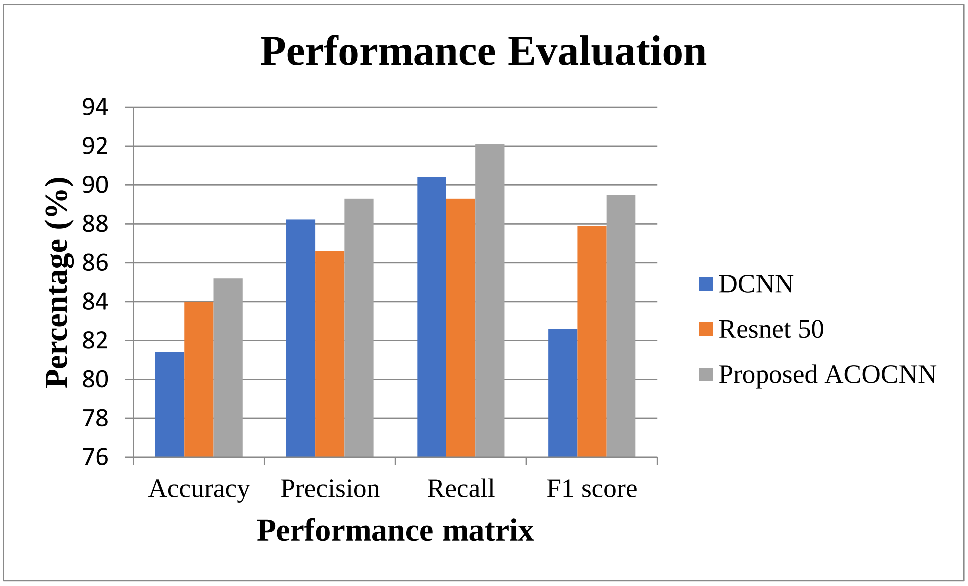

Figure 3: **Performance Evaluation of the Proposed ACOCNN**

The proposed ACOCNN model's performance evaluation is shown in Figure 3.

5. Conclusion

Melanoma, a type of skin cancer with high mortality rate is increasingly frequently all over the world. The proposed method utilizes the dermoscopic images for the detection and classification of the affected areas in the skin. The dermoscopic images are noise-free due to the implementation of the Gaussian filters. A better region-growing method was applied to segment the lesions afterwards. Ant Colony Optimization was employed to extract the features in the images. The proposed ACO-CNN performed much better than that of the existing algorithms for melanoma skin cancer diagnosis in terms of segmentation and classification. The detection of melanoma skin cancer has been discussed in this framework via improved segmentation and classification. Efficiency can be increased by deploying techniques from deep learning that make use of convolutional neural network and long short -term memory.

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