# DETECTION OF MELANOMA USING IMAGE PROCESSING TECHNIQUES

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*Abstract* - **The aim of this project is to create an automated melanoma detection system utilizing digital image processing and machine learning. Following the segmentation of the provided dermoscopic pictures, the damaged skin cells' features are extracted using a feature extraction technique. The stratification of the extracted features is done using a convolutional neural network classifier.The system will be able to identify any early melanoma symptoms, so that the user can immediately address the issue before the cancer cells multiply rapidly.**

## 1. INTRODUCTION

Computational intelligence (CI) and its wide applications in biomedical engineering provide cancer, genetic data, genomics, biometric systems, ontology construction, structural prediction, and more. protein architecture, biomedical data analysis and biomedical electronics. CI is the study of the design of an intelligent agent, that is, a system that can act on purpose they do what they think is appropriate for the purpose and circumstances; they are flexible to changing goals and environments; they learn from experience and they make choices that are consistent with finite computations and cognitive limitations. Furthermore, rapid advances in research and computer-aided surgery in the cellular, tissue, molecular and engineering fields make CI an inevitable part of biomedical applications. The CI model offers more advantages to improve and sustain the field of biomedical engineering. Malignant growth of contrast skin with other tumor types is a major factor in exacerbation of medical disease [3-5]. In the early years, melanoma was a rare malignancy, but today the total number of melanoma cases is increasing dramatically. To quickly identify skin cancer and solve the above problems, there is a comprehensive research solution by providing a computer algorithm that analyzes the image. Most algorithmic solutions are parametric, meaning they need normally distributed information. Because of the uncontrollable nature of the information, this method will not be sufficient to accurately identify the disease. But the non-parametric solution does not depend on the constraints that the information is in a standard distribution format. With current advances in software and hardware engineering, DL is emerging as an efficient mechanism for learning features. Feature engineering is a process of extracting and defining features by human expertise, which is a tedious and tedious task. The DL method eliminates the need for feature engineering because it can automatically learn and extract meaningful features from raw information. DL has transformed many different fields, especially computer vision. In Biomedical Engineering, DL represents a significant achievement in the present study. Automatic classification of skin lesions by imaging is a difficult process due to the slight variation in the appearance of the skin lesions. Deep convolutional neural networks (DCNNs) show potential for generic and highly variable tasks across many detailed feature classes. Armed with a deep neural network, the mobile device has finally extended the reach of dermatologists outside the hospital. CNN achieved comparable performance to individual testers on both tasks, demonstrating the AI's ability to classify skin lesions on par with dermatologists. This study presents efficient CI-based melanoma detection and classification using dermatoscopy imaging (CIMDC-DI) technique. The proposed CIMDC-DI model includes bilateral filtering-based noise reduction with image segmentation based on clustering of k-fuzzy vehicles (FKM) as a pre processing step. In addition, a NasNet-based feature extractor with random gradients is applied to feature extraction. Finally, realizing the importance of parameter optimization in improving model performance [12, 13], manta ray search optimization algorithm (MRFO) with cascade neural network (CNN) used for the classification process. To ensure the best results of the CIMDC-DI technique, a full-scale simulation analysis was performed and the results were evaluated in separate aspects.

## 2. RELATED WORKS

Lai et al presented a technique that combines genomic data, disease networks, and DL techniques to classify melanoma patients on prognosis, assessing the influence of genomic features on the classifiers. and provide an explanation of the influential feature. He combined the genome

data with the melanoma network and performed an AE approach to identify subgroups of patients with TCGA melanoma. This technique uses the community identified from the network to effectively reduce the size of the genomic data to the patient score profile. Lafraxo et al.

propose a CCN-based deep learning model to automate the classification of benign or malignant skin lesions in skin imaging. Furthermore, the performance of the model is improved by using three techniques such as data augmentation, regularization and dropout to avoid over-equipped. Shorfuzzaman presented an interpretable CNN-based stacked aggregation framework for detecting melanoma skin cancers at earlier stages. In the stacked aggregation framework, a transfer learning (TL) method was used where multiple CNN submodels performing similar classification tasks were collected. A new technique called meta-learning uses each sub-model forecast and generates the latest forecast results. Kim and associates. presented a new technique for unsupervised hair extraction and its estimation on a true melanoma dataset. In a generic adversarial learning infrastructure, the hair feature is considered with easy coarse-grained labels using binary classifiers. In addition, a key feature of well-maintained lesions due to loss of L1 norm reproducibility is minimized based on Laplace noise assumptions. In, a DL-dependent melanoma segmentation method was presented. Combined with post-processing methods, the presented modified U-net network is extremely efficient from the established lesion segmentation. Hagerty et al. Introduction to integrated engineering common image processing with DL . merge function in individual actions. It is proposed that the two approaches, with distinct error profiles, are synergistic. The conventional image processing arm using 3 manuals biomimetic image processing elements and a drug data element. In a new proposal, the DCNN method for classifying skin lesions as malignant and benign on dermoscopy images has been presented by creating multiple connection blocks to allow massive feature data to be transmitted directly. with the network. All blocks in the network use distinct parameters such as number of nuclei, filter size, and stride to extract low- and high-level feature data in lesions.

## 3. Proposed Model

This study developed a novel CIMDC-DI approach for melanoma identification and classification using dermoscopic images. The presented CIMDC-DI model involves BF-enabled noise reduction, FKM segmentation, NasNet feature extraction, CNN classifier, and MRFO parameter optimization. The utilization of the MRFO algorithm assists in the effectual choice of parameter values involved in the CNN model. Figure illustrates the overall block diagram of CIMDC-DI technique.

- **Bilateral Filtering:** At the primary level, the BF technique is used to eradicate the occurrence of noise in dermoscopic images. Dermoscopic images comprise noises like Gaussian, salt pepper noise, and so on [20]. Extracting the noise preserves the data similar to the input data. The BF approach was utilized to denoise this input image. Without utilizing the smoothing edge, the spatial weight averaging was executed by BF. This filtering combines two Gaussian.

- **FKM-Based Image Segmentation:** In order to identify the lesion regions in the dermoscopic images, the FKM tech nique has been exploited. The segmentation is employed by an FKM on the extracted set of the melanoma cancer for separating the healthy pixel in the melanoma pixel. The major reason for selecting the FKM over K-means clustering is that K-means clustering is the hard kind of clustering in which one instance belongs to a single cluster; however, in FKM, one instance belongs to one or more clusters; hence, it performs well for overlapped information.

- **Feature Extraction:** At the time of generating feature vectors, the segmented images are fed into the NasNet model. CNN comprises input and output layers with many hidden convolutional layers. The NASNet model is inspired by Neural Architecture Search (NAS) model [22], which exhibits high flexibility and scalability in terms of compu tation resources and parameters. It has been trained on the chosen ImageNet database which and is optimized. It comprises a collection of filters, which are then employed to RGB pixel values of the image via sliding window manner. The dot product of filters and input pixels is determined. The feature map is reached in a 2-dimension activation map of the filter. Figure 2 illustrates the structure of cascaded NN. It learned the features need to be activated if identified features in the input are attained. Then, the convolutional function is carried out on all feature maps. It enables CNN in learning various feature map weights and biases. Then, max pooling operation can be utilized for reducing the feature map size. Next to every convolutional layer, subsampling layer is attained which enables to reduction of the size of the convolutional map.

## 4. Problem Statement

- Melanoma is the most serious category of skin cancer.
- It generally develops in melanocytes - the cells that produce the pigment melanin - which gives our skin its color.
- Additionally, melanoma can develop in your eyes and, very rarely, inside your body, like in the throat or nose.
- Although the precise causation of melanoma is unknown, exposure to ultraviolet (UV) radiation from sunshine, tanning beds, or tanning lamps increases the risk of acquiring the disease.
- Melanoma appears to be rising among those under 40, particularly women.
- The detection and successful treatment of malignant changes prior to the development of the cancer can be facilitated by being informed of the warning symptoms of skin cancer.

- If melanoma is found early on, it can be successfully treated.

## 5. Methodology

- The BF approach is used to reduce noise in dermoscopic images at the most fundamental level.
- Dermoscopic images include noises like salt and pepper and Gaussian noise, among others.
- The data are kept close to the input data after the noise has been removed.
- This input image was denoised using the BF method.BF performed the spatial weight averaging without using the smoothing edge.
- In order to provide filtering in both the spatial and intensity domains, this filtering combines two Gaussian filters; another one is already in operation.
- The segmented images are loaded into the NasNet model to create feature vectors.
- Along with several hidden convolutional layers, CNN consists of input and output layers.

## 6. Performance Vallidation

In this section, the experimental validation of the proposed model is performed using three challenging benchmark datasets [25], as shown in Table 1. The results are inspected with 70% of training data and 30% of testing data. A few sample images are demonstrated in Figures portrays the set of three confusion matrices attained by the CIMDC-DI model on three datasets. On the ISIC2016 dataset, the CIMDC-DI model has recognized 41 images of melanoma and 47 images of benign. Moreover, on the ISIC2017 dataset, the CIMDC-DI algorithm has rec ognized 55 images of melanoma and 62 images of benign. Furthermore, on the ISIC2017 dataset, the CIMDC-DISEC uses the IEEE electronic copyright form. EDAS will provide a link to the form when you upload your final paper. You MUST sign the copyright over to IEEE to have your paper included in the proceedings.

You MUST receive any client approvals of your paper as soon as possible to avoid proprietary/IP issues that could prevent your paper from being presented at ISEC approach has recognized 67 images of melanoma and 77 images of benign. Table 2 provides detailed melanoma classification out comes of the CIMDC-DI model on the ISIC2016 dataset. The results indicated that the CIMDC-DI model has reported electual outcomes on both training and testing datasets. Forinstance, with 70% of the training dataset, the CIMDC-DI model has resulted in average accuy, precn, recal, and Fscore of 97.78%, 97.77%, 97.77%, and 97.77%, respectively. Besides, with 30% of the testing dataset, the CIMDC-DI (Table 3) model has accomplished average accuy, precn,recal, and Fscore of 94.29%, 94.36%, 94.36%, and 94.29%, respectively.

Table 3 depicts a brief melanoma classifcation outcome of the CIMDC-DI technique on ISIC 2017 dataset. The results exposed that the CIMDC-DI algorithm has reported electual outcomes on both training and testing datasets.

For instance, with 70% of the training dataset, the CIMDC-DI methodology has resulted in average accuy,precn, recal , and Fscore of 96.79%, 96.85%, 96.84%, and 96.79% correspondingly. Finally, with 30% of the testing dataset, the CIMDC-DI technique has accomplished an average accuy, precn, recal, and Fscore of 97.50%, 97.54%, 97.45%, and 97.49%, respectively.

## 7. Conclusion

In this study, a novel CIMDC-DI algorithm was developed for melanoma identification and classification using dermoscopic images. The presented CIMDC-DI model involves BF-enabled noise reduction, FKM segmentation, NasNet feature extraction, CNN classifier, and MRFO parameter optimization. The utilization of the MRFO algorithm assists in the electual choice of parameter values involved in the CNN model. To ensure the better outcomes of the CIMDC-DI technique, a wide-ranging simulation analysis was implemented and the results are assessed under distinct aspects. A wide-ranging simulation analysis was executed, and the results reported the betterment over the recent methods with the maximum accuracy of 97.50%. Thus, the IMDC-DI model can be exploited as a procient tool for real-time melanoma classification. In the future, the CIMDC-DI model can be extended to the incorporation of DL-assisted segmentation approaches. Besides, a fusion ased ensemble classifier model can be developed for melanoma classification.

### Data Availability

Data sharing is not applicable to this article as no datasets were generated during the current study.

### Ethical Approval

This article does not contain any studies with human participants performed by any of the authors.

### Consent

Not applicable.

### Conflicts of Interest

The authors declare that they have no conflicts of interest to report regarding the present study.

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