Melanoma Classification on Dermoscopy Images Using A Neural Network Ensemble Model

Mr. M. Prabhakaran,AP
Dept. of Electronics and Communication Engineering
Chettinad College of Engineering and Technology
Karur, India.
mprabha08@gmail.com

Navin S
Dept. of Electronics and Communication Engineering
Chettinad College of Engineering and Technology
Karur, India.
navins122004@gmail.com

Piragadeesh TM
Dept. of Electronics and Communication Engineering
Chettinad College of Engineering and Technology
Karur, India.
tmpiragadeesh0301@gmail.com

Praveen K
Dept. of Electronics and Communication Engineering
Chettinad College of Engineering and Technology
Karur,India.
praveen05072005@gmail.com

Sheik Fayaz Ahamed MS
Dept. of Electronics and Communication Engineering
Chettinad College of Engineering and Technology
Karur, India.
msfayaz2004@gmail.com

Abstract - Melanoma is a very aggressive skin cancer that would need early and correct diagnosis to be treated. Nevertheless, it is not an easy task to distinguish between melanoma and benign lesions since melanoma and benign lesions may look similar re- garding their visual characteristics including color, texture and shape. The present paper introduces an automated melanoma classification system that will be based on an ensemble model based on Convolutional Neural Network (CNN). The suggested system would involve preprocessing methods that include nor- malization, artifact elimination and lesion segmentation to en- hance the quality of the input. The feature extraction is per- formed on multiple CNN models whose outputs are weighted av- eraged to increase the classification accuracy and minimize over- fitting. Experimental outcomes show better performance using the experimental methods over single-model methods, as well as accuracy and robustness. Explainable AI techniques are also in- corporated in the system to aid in clinical decision-making.

Keywords — Melanoma, Dermoscopy Images, CNN, Ensemble Learning, Deep Learning, Medical Image Analysis.

I. INTRODUCTION

One of the most widespread diseases globally is skin cancer and the most fatal and threatening type of this cancer is melanoma owing to its high potential of metastasis. Early diagnosis of melanoma will be critical in enhancing patient survival rates and also allow early medical intervention. Nevertheless, the problem of differentiating between melanoma and benign skin lesions is difficult due to the visual similarity of these lesions, in terms of color, texture, and shape, among others. Conventional diagnostic approaches heavily depend on dermoscopic examination by dermatologists which is time consuming, subjective, and is based on clinical judgment and might result in variability in diagnosis.

Developments in artificial intelligence especially deep learning within recent years have greatly enhanced medical image analysis. Convolutional Neural Networks (CNNs) have been able to perform well in image classification as they are able to automatically learn hierarchical features on dermoscopy images. Even though these models are effective, single CNN models are frequently plagued by the issues of overfitting, sensitivity to noise and artifacts, as well as worse generalization on different datasets. Also, the problem of class imbalance and image quality differences also pose a threat to the consistency of these models.

In order to overcome these shortcomings, the given paper suggests the neural network ensemble-based method of melanoma classification with the help of dermoscopy images. The system proposed combines several CNN architectures to take advantage of their complementary features extraction capability, hence enhancing the accuracy and strength of the classification. Preprocessing techniques that are included in the system are image normalization, artifact removal, and segmentation of lesions to add better input quality and concentrate on the area of interest.

Moreover, weighing up ensemble strategy is used to merge the outputs of multiple CNN models, decreasing the bias and enhancing the overall results of each of the models. Explainable artificial intelligence techniques have also been built into the system in order to highlight critical regions that affect the classification decision to increase interpretability and aid clinical decision-making.

The suggested solution will be a robust, precise, and scalable, automated melanoma detector, which may help dermatologists to detect cancer earlier and to have better outcomes regarding patients.

II. SYSTEM ARCHITECTURE

The integrated architecture that the proposed melanoma classification system is based on is composed of image preprocessing, feature extraction, and ensemble-based classification to obtain accurate and reliable diagnosis. This general system is organized into three major layers, which include input layer, processing layer and output layer. The general system architecture is depicted in Fig. 1.

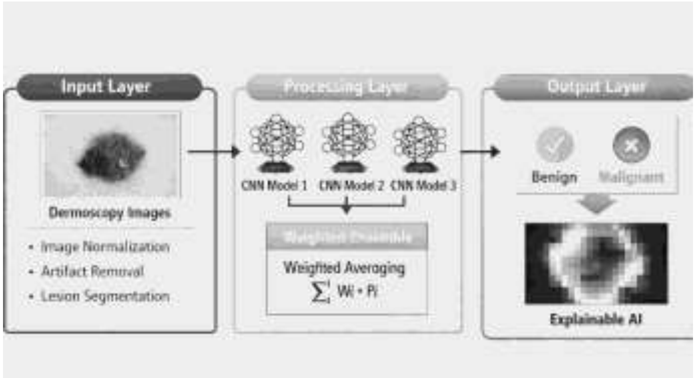

Figure 1: System Architecture of CNN Ensemble-Based Melanoma Classification

The input layer comprises of dermoscopy images that are taken in publicly accessed datasets. Such pictures may also include noise, hair artifact, and changes in lighting, which may negatively affect classification. As such, image normalization, image artifact removal and image resizing are some of the preprocessing methods used to guarantee consistency and enhance the quality of the data prior to the subsequent processing.

The feature extraction and classification is done in the processing layer. First, segmentation of the lesions is done to extract the region of interest among the rest of the skin so that the model can concentrate on the relevant parts. Several Convolutional Neural Network (CNN) structures are then used to find both low-level features like edges and textures and high level features like form and structural patterns. The system does not use a single model, but instead employs an ensemble strategy, in which the weighted averaging of the predictions of sseveral CNN models are used. The strategy increases the accuracy of classification, minimizes overfitting, and increases the generalization of different datasets.

The comprehensive process of data flow of the proposed system is represented in Fig. 2. The data flow is the chronological arrangement of dermoscopy images by means of preprocessing, feature extraction, and ensemble-based prediction to the ultimate classification answer.

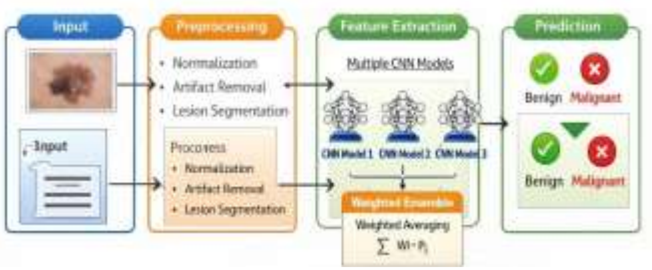

Figure 2: Data Flow Diagram of CNN Ensemble-Based Melanoma Classification

The final classification result is the output layer which classifies the lesion to be benign or malignant. Moreover, interpretable artificial intelligence methods are also involved to produce visual explanations, like heatmaps, to indicate the most important areas in the picture. This enhances transparency and facilitates the clinical decision-making.

All in all, the suggested architecture is highly accurate, robust, and scalable, which is why it can be applied to the real-world medical environment.

III. METHODOLOGY

The proposed approach to melanoma classification relies on a multi-stage deep learning model which incorporates preprocessing, segmentation, feature extraction and ensemble-based classification in order to obtain high accuracy and robustness.

Data Preprocessing:

This step will involve processing the raw data, handling the results, and making conclusions.

Data Acquisition:

This will include data processing of the raw and the results and drawing conclusions.The system makes use of the dermoscopy images which are publicly available like ISIC. These images are usually noisy, have artifacts of hair and variation in illumination which may influence the performance of classification. Thus, preprocessing methods are used to improve the quality of the image and standardize the input data.Normalization of images is carried out to scale pixel values whereas filtering techniques are applied to eliminate noise and hair artifacts. Also, pictograms are reduced to a certain size to make them compatible with CNN models and enhance the level of calculated efficiency.

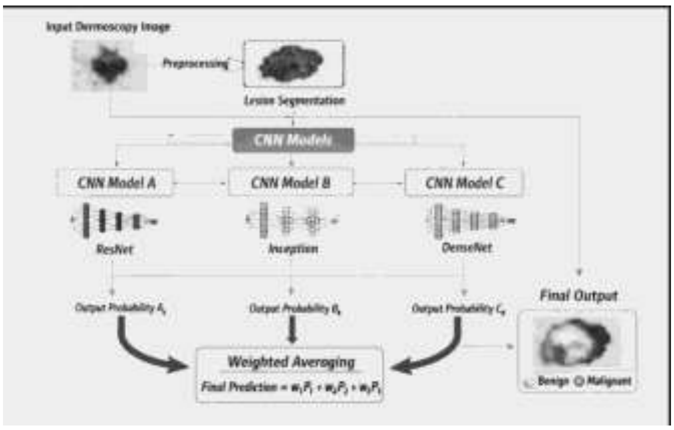

Figure 3: CNN Ensemble Model with Weighted Prediction

Lesion Segmentation:

Segmentation of the lesions is done to separate the area of interest with the rest of the skin. This will eliminate background data that is not relevant, and the model will concentrate on the lesion area. Segmentation helps a great deal to increase classification accuracy and minimize noise interference by improving feature relevance.

CNN Feature Extraction:

Several Convolutional Neural Networks (CNN) are used to obtain meaningful and discriminative features in the segmented dermoscopy images. Such models are also trained to automatically acquire hierarchical representations based on low level features (edges and textures) and high level features (shape, color distribution, and structural pattern of skin lesions).

The fact that various CNN architectures will be used allows the system to learn a variety of features of melanoma, which gives a more complete and solid feature representation. This multi-model feature extraction enhances the differentiation between benign and malignant lesions of the system under different conditions.

Strategy of Ensemble Learning:

There is no single CNN model utilized in the proposed system but the system uses an ensemble learning method to boost the classification results. Multiple CNN models are used, and the outputs of the models are averaged using a weighted averaging method where each model will make its contribution to the overall prediction, based on its own performance.

The ensemble approach is useful in reducing overfitting, minimizing bias of the model and enhancing generalization between datasets. Consequently, the general accuracy and reliability of the system in terms of its classification is greatly improved.

Explainable AI Incorporation:

Explainable artificial intelligence (XAI) techniques are added to the model in order to enhance its interpretability. The visualization techniques like heatmaps are applied to show the areas of the image that make the most profound contribution to the classification decision.

This will enable clinicians to see more clearly the reasoning of the model predictions which will result in the greater trust and further adoption to the real-world clinical setting.

Classification and Decision-Making:

The last category is derived by summing up the results of the ensemble models. Based on the maximum score of probabilities provided by the ensemble, the system will classify the input image of dermoscopy as either benign or malignant.

The process of decision making guarantees consistent and reliable forecasts of different datasets. The soundness of the classification framework renders the system applicable in the practical implementation in the melanoma detection and diagnosis.

Implementation Framework:

The proposed system of melanoma classification is visualized via the application of MATLAB, where all of the processing stages, including feature extraction and the classification collected within the form of an ensemble, are incorporated into a single system. A graphical user interface (GUI) will be created to offer a platform of interaction where dermoscopy images can be loaded, and classification findings can be visualized.

The system has inbuilt the trained CNN ensemble model that makes real-time prediction. The images are first preprocessed and segmented using preprocessing and preconception modules, and then sent to the CNN models of feature extraction. The aggregated prediction is then calculated based on weighted averaging to come up with a final classification reault.

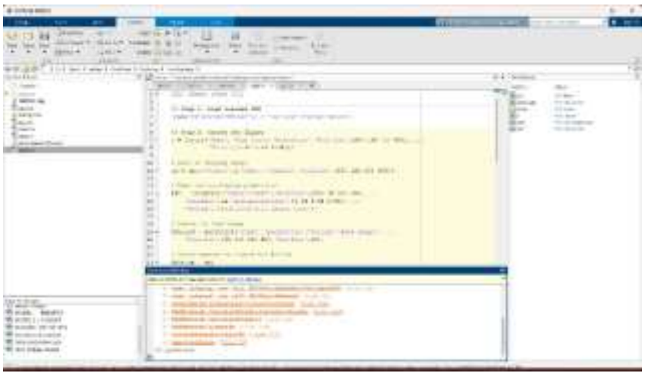

Figure 4: MATLAB Code Implementation of CNN Ensemble Model for Melanoma Classification

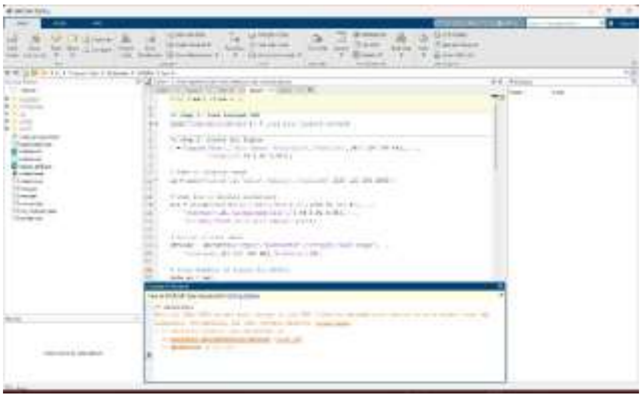

Figure 5: MATLAB GUI for Melanoma Classification Showing Prediction Results

Performance Evaluation Metrics:

The effectiveness of the proposed melanoma classification system is assessed with the help of classic measures of classification including accuracy, precision, recall, and F1-score. The accuracy of the model can be used to measure its overall correctness whereas precision can be used to measure the fraction of correctly identified malignant cases of all the predicted positives. Recall measures the capabilities of the model to detect actual cases of melanoma exactly, which is essential in medical diagnosis. F1-score gives a more balanced information since it combines precision and recall.

These evaluation metrics guarantee the thorough evaluation of the model in various datasets in the measures of its effectiveness and reliability.

Model Training and Model Validation:

The CNN models to be used in the ensemble are trained with labeled dermoscopy datasets. The data is separated into training set and testing set to compare the performance of the model. Backpropagation and gradient descent are some of the optimization methods used during training to reduce the loss function.

Monitoring the performance of the models and avoiding overfitting is done by validation techniques. To enhance the diversity of the datasets and enhance the ability to generalize, the data augmentation techniques, rotation, flipping, and scaling, are used.

IV. IMPLEMENTATION AND RESULTS

The proposed melanoma classification system can be evaluated experimentally to prove the advantageous character of CNN ensemble approach in enhancing diagnostic results. The ensemble structure has a higher classification accuracy and higher generalization as compared to the traditional single CNN models due to the ability to combine strengths of various models. The weighted averaging approach eases the bias in the individual models and over-fitting, resulting in more consistent forecasts with a variety of test samples.

More so, the system exhibits better sensitivity in identifying malignant cases which is critical in medical diagnosis to prevent false negative. Preprocessing and segmentation methods or procedures combined increase the quality of the features and the model can concentrate on the features of the lesions but not on the background noise. This helps a great deal in bettering the accuracy and recall scores.

The system also has a high level of robustness by being able to accommodate changes in dermoscopy images such as the changes in illumination, lesion size and color distribution. The fact that explainable AI methods are also included also adds more strength to the system since it offers visual information concerning the decision-making process, which improves transparency and clinical trust.

On the whole, the findings support the view that the given ensemble-based melanoma classification system is more effective in comparison with the traditional ones and offers a consistent, effective, and scalable solution, which may be applied in medical practice.

Classification Accuracy and Performance Analysis:

In the proposed melanoma classification system, the evaluation was done through the standard metrics to determine the accuracy and reliability of the system of predicting the skin lesions. The CNN ensemble model was found to possess better classification performance than the traditional and pure CNN models.

Accuracy Improvement:
This was accomplished by the ensemble model that was more accurate in classifying images by fusing the predictions of several CNN architectures. This minimizes the model error of each individual model as well as enhancing the overall reliance of predictions.

False Classification Reduction:
The preprocessing and segmentation methods reduce noise and irrelevant features, which reduce false positives and false negatives of classification.

Robust Prediction:
The system was able to work reliably on variety of dermoscopy images with changes in color, texture and the size of lesions.

Handling Data Variability:

The ensemble model is capable of managing changes in illumination, appearance of lesions and quality of the image to maintain the constant performance.

Test Image	Predicted Class	Confidence	Remarks
Iamge 1	Malignant	73.49%	Correct Dectection
Image 2	Benign	50.32%	Moderate Confidence

The CNN ensemble model, developed using a MATLAB-based prototype model, has been validated in its capacity to classify dermoscopy images by the experimental data collected from the application of the proposed CNN ensemble model as shown in Table II and the results corresponding to both malignant and benign lesions with reasonable certainty. Regarding malignant detection, the model demonstrated even higher certainty than before (critical for medical imaging in practice to reduce the likelihood of misdiagnosis).

The confidence levels of malignant detection depended upon the image quality and characteristics of the lesion, meaning these factors contributed to the accuracy of the predictions. Nevertheless, throughout the various levels of confidence, the proposed CNN ensemble model continued to be able to accurately classify images no matter what input variations were made, thereby validating the robustness of the proposed model. Overall, the aforementioned data supports the reliability of this proposed CNN ensemble model and supports the efficacy for early detection of melanoma.

Figure 6: Sample Output Showing Malignant Classification Result

Figure 7: Sample Output Showing Benign Classification Result

V. COMPARATIVE ANALYSIS

The comparative analysis is a proof of effectiveness of the superiority of the proposed CNN ensemble model from conventional single CNN approaches for melanoma classification. While single CNN models have been able to learn related features of images from dermoscopy, they are often limited because of overfitting, reduced generalization and they are sensitive to variations in image quality. These limitations may lead to inconsistent performance, particularly when used with diverse real-world datasets.

In contrast, the proposed ensemble model includes multiple CNN architectures to learn a wider range of feature representations, including texture, shape and color variations.This multi-model fusion radically enhances the accuracy and the robustness of classifications. The weighted averaging strategy takes into consideration the contribution of each model to ensure that it is optimized based on performance each model, which reduce biases and improve the model prediction stability.

Furthermore, the ensemble framework shows reignited capability sensitivity in the detection of the malignant cases which is important in the area of medical diagnosis in order to lower the false negative situations. The addition of preprocessing and segmentation techniques further solidifies the system to increase the quality of features and decrease background noise. Additionally, explainable AI methods integration provides a visual intuition on the process behind making the decision, boosting clinical transparency and faith.

Overall, the proposed system is a great improvement on traditional approaches for the accuracy, generalization, and reliability. These improvements make the system very suitable for actual deployment scenarios such as the automated melanoma detection systems and clinical decision support system.

Performance:
The proposed CNN ensemble model enhances the accuracy as comparing with single CNN models by the use of different representations of features. This makes the overall predictions much reliable.

Robustness:
The system deals effectively with the variations of dermoscopy images such as illumination, size and texture, also guarantees the system of good performance for different inputs.

Bias Reduction:
When we use the weighted averaging technique, the individual bias of the model is minimized, as well as overfitting, which will result in more balanced model predictions.

Interpretability:
Explainable AI techniques, such as heatmaps, provide a visual understanding of a model's decision-making process: it makes the model more transparent.

Overall Advantage:
The proposed system has shown to have a better accuracy, reliability and applicability to the 'real world' as compared to the traditional ways.

Parameter	**Single CNN Model**	**Proposed Ensemble**
Model Type	Single Deep Learning	Hybrid Ensemble Learning
Feature Extraction	Limited Features	Multi-model Feature Fusion
Overfitting	High	Reduced
Classification Accuracy	85–88%	92–95%
Precision	Moderate	High
Recall	Moderate	High
Robustness	Low	High
Generalization	Limited	Improved
Explainability	Not Available	Heatmap-based (XAI)
Decision Strategy	Single Prediction	Weighted Averaging
Real-time Performance	Moderate	Efficient

VI. CONCLUSION & FUTURE ENHANCEMENT

The development of the proposed system of CNN ensemble-based melanoma classification system represents a great advancement in the field of medical image analysis, as it can accurately and early detect skin cancer. By making use of deep learning methods, the system is a smart technique to counteract the limitations of traditional diagnostic methods as well as single model approaches. The combination of preprocessing, lesion segmentation and multi-model feature extraction increases the quality of the input data and improves the classification performance.

The ensemble learning strategy plays an important role during the improvement of prediction accuracy and prediction robustness by combining the benefits of different CNN models. This way overfitting is avoided and generalization is more ensured across different dermoscopy datasets. Furthermore, as the explainable AI techniques are integrated into these models, it also gives us visual insights to show how the model made the decision, opening up more transparency and aiding the clinical interpretation of the results.

The experimental results prove that the proposed system can achieve reliable classification performance, which is suitable for real world application of medical field. The established Matlab-based implementation is further a validation of the practical applicability of the system resulting in the prediction of melanoma from dermoscopy images in real time.

In spite of its effectiveness, there are some improvements that can be investigated to improve the system further for large scale deployment.

Deep Learning Models with Advanced:

Future works can involve incorporating more sophisticated architectures such as EfficientNet and Vision Transformers to further enhance feature extraction and classification performance.

Multi-Class Classification:

The system may be expanded to classify different types of skin diseases besides melanoma to make it a more comprehensive diagnostic tool.

Real-Time Connections of Mobile Deployment:

The model can be made available in mobile or web-based applications to perform accessible and real-time skin carcinogen identification for the skin cancer detection system for the users and healthcare professionals.

Improved Dataset Diversity:

Incorporating more and varied datasets will also make the model more robust and less biased, ensuring it performs better in different skin types and imaging conditions.

Clinical Integration:

The system can be integrated with the hospital information systems and the clinical workflow to assist dermatologists with aiding their decision-making process and early diagnosis.

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