



Original Article

Enabled Deep CNN Model for Skin Cancer Classification Using Dermoscopic Images

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Abstract - Skin cancer is identified as one of the most common and dangerous dermatological conditions, and it is essential that it is diagnosed early and correctly to significantly increase patient survival rates. Although dermoscopic image analysis with deep learning has been proven effective for dermoscopic image analysis, several problems like non-relevant background characteristics, poor feature extraction, and lack of explanations still exist. In light of these limitations, this paper presents an attention-assisted hybrid deep learning framework for dermoscopic image classification tasks to detect and classify skin cancer based on dermoscopic images. The proposed deep learning framework combines EfficientNet-B4 and CBAM for deep feature extraction and lesion-associated channel and spatial cues. Moreover, GWO is utilized for the optimization of features and parameters, which further leads to faster convergence and generalization capabilities. The proposed framework is evaluated on a publicly available dermoscopic image dataset, and results show that it outperforms existing deep learning and non-attention models with higher classification accuracy at 98.7 percent. The proposed framework is a highly accurate and interpretable system that utilizes deep learning and GWO optimization and is efficient and practical for real-world application in dermoscopic image analysis tasks like computer-assisted diagnosis for skin cancer.

Keywords - Cancer Classification, Dermoscopic Image, Melanoma Classification, CBAM, GWO, XAI, Automated Lesion Analysis, Multi-Class Classification.

1. Introduction

Skin cancer represents one of the most prevalent types of cancer throughout the world, becoming an important public health issue because of its rapid growth in incidence rates, along with the potential danger of death, especially in the case of malignant melanomas [1]. Early diagnosis represents an important factor for improving the efficiency of patients' care because of the potential for decreasing the cost of treatment by providing an early intervention opportunity for doctors [2]. Another important issue associated with dermoscopic analysis is the fact that doctors are still very dependent on experience, especially when dealing with inter-observer variations. Recently, DL, including CNNs, has proved to be very successful in analyzing medical images, including skin cancer images [3]. The CNN-based systems can automatically extract hierarchical features from dermoscopic images with no need to design feature extraction by humans [4]. Although these methods are successful, there are some challenges, including an insufficient focus on regions of interest, susceptibility to artifacts in the background, and reduced explainability of decision-making, in traditional CNN models that restrict their use in practical environments where explainability and robustness are mandatory [5]. These limitations can be overcome by using attention mechanisms that help the model learn the most discriminative features by guiding it to focus on diagnostically important regions.

Among these, CBAM has emerged as one of the frontiers with its lightweight design and refined channel-wise and spatial feature representations [6]. The effectiveness of deep learning models, on the other hand, is much dependent on optimal feature selection and hyperparameter tuning. To address these challenges, metaheuristic algorithms, inspired by natural phenomena, have come up as proficient tools to improve convergence behaviour and generalization capability. Particularly, Grey Wolf Optimization has shown superior performance in optimizing complex, high-dimensional search spaces [7]. Besides accuracy, interpretability has been an essential requirement for medical AI systems. XAI methods are designed to provide clinicians with insights into model predictions by visualizing how the model came to its decision [8].

The most commonly used techniques called Grad-CAM offers class-discriminative visual explanations by highlighting the lesion areas that contribute significantly to the classification result. Such knowledge is crucial for understanding model reliability, thus for the clinical adoption of a model. With this background, this study presents an attention-assisted hybrid deep learning approach using dermoscopic images of skin cancer. The proposed approach uses the power of efficient extraction of deep skin cancer features by applying EfficientNet-B4, skin cancer feature enhancement using CBAM with attention mechanisms, and GWO to optimize skin cancer features as well as hyperparameters. Softmax is also employed to classify

multiple skin cancer lesions. Grad-CAM is also employed as a visualization technique in making decisions in skin cancer classifications [9]. Results clearly show that the proposed approach attained a high skin cancer classification accuracy of 98.7% in comparison to other approaches using CNN. Hence, this proposed approach is effective in clinical skin Cancer Diagnosis. Most state-of-the-art studies rely on a single backbone CNN architecture without any adaptive attention mechanism that ensures optimal localization of lesion boundaries and visually similar confusion classes like melanoma and benign nevi [10].

2. Related Works

More recently, deep learning algorithms have gained significant attention in the automatic detection of skin cancer based on dermoscopy images. In the past, mainly classical machine learning models were used along with carefully designed features like color, texture, and shape features [11]. Even though classical models were successful in their first achievements, their results were highly sensitive to feature engineering and were not robust enough in various setups. With the introduction of convolutional neural networks, better results were achieved in the classification stage through the extraction of features from the raw dermoscopic images [12]. Various works have also used popular architectures of CNNs such as VGG, ResNet, DenseNet, and Inception for skin cancer classification. These architectures proved to have good feature extraction capabilities and improved diagnosis performance over traditional approaches. However, these architectures also caused an increase in computational complexity and overfitting, especially when small quantities of medical data are involved [13]. Additionally, in general CNN architectures, an equal attention level is paid to all spatial areas, which results in misclassification owing to artifacts such as hair, white bubbles, and illumination in dermoscopic images [14].

Attention mechanisms have hence been incorporated into the skin cancer classification framework to tackle these challenges. Attention modules help networks focus on the lesion-relevant regions and suppress background noise. Various works reported considerable improvement in performance that integrated spatial attention, channel attention, and their hybrid attention strategies [15]. Specially, lightweight attention modules like CBAM have been widely used because they can enhance the discriminative feature learning of models without adding too many model parameters. However, most of the attention-based models still depend on manually selected hyperparameters, which reduces their generalization capability [16]. Recently, metaheuristic optimization algorithms have been explored for boosting deep learning performance in medical image analysis. Feature selection and hyperparameter tuning with PSO, GA, and GWO have been conducted. Of the many, GWO has demonstrated a sound convergence behaviour and robustness for high-dimensional optimization problems [17].

However, only a very few attempts have effectively integrated meta-heuristic optimization with attention-enabled CNN architectures in dermoscopic image classification. In

addition to optimizing performance, model interpretability has rapidly emerged as an essential research focus in medical AI [18]. Explainable Artificial Intelligence techniques target improved clinical understandings between deep learning predictions. Various techniques such as Grad-CAM, LIME, and SHAP have been used for visualizations of model decision regions in analyses of skin lesions. Grad-CAM has been widely adopted because it is simple and highly effective at generating class-discriminative heatmaps [19]. Despite this progress, most existing works have tended to treat explainability as a kind of post-processing step rather than an integral core component of the diagnostic framework. In other words, though various studies have established the efficacy of deep learning, mechanisms of attention, optimization algorithms, and explainability techniques separately, their combined integration in a single framework remains scant [20].

3. Methodology

The proposed methodology presents an attention-assisted, optimization-aided, and explainable deep learning approach for precise skin cancer classification based on dermoscopic image analysis. The approach comprehensively encompasses image processing for improved visualization, extraction of robust deep-level features with an EfficientNet as the base model, attention-assisted refining of the relevant lesion areas based on CBAM attention, and optimization for improved hyperparameter and feature selection with metaheuristic optimization. A Softmax-based classifier is used for multi-class lesion prediction, and Grad-CAM is used as an additional component for class-wise discriminative attributive visual explanations, thereby facilitating high-performance diagnostics and explainability as well.

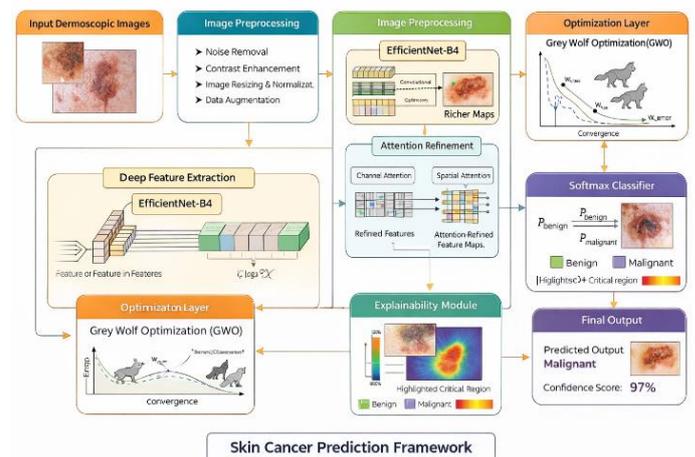


Fig 1: Skin Cancer

The deep-level feature extraction phase makes use of the EfficientNet-B4 model, wherein the compound scaling technique is used by the network for effectively balancing depth, width, and resolution while learning complex-scale dermoscopic pattern variations such as variations in skin color, border irregularities, and asymmetrical textures. CBAM attention sequentially performs channel and spatial

attention in an attempt to allow the network to narrow down lesion-level relevant areas while discarding background information. In addition, the application of the GWO algorithm is used as a metaheuristic approach in the optimization procedure to fine-tune the selection of the most optimal features and the learning rate and dropout probability hyperparameters. Finally, the results of the classification are obtained by the Softmax function in the fully connected layers.

Table 1: Dataset Process

Category	Subcategory	percentage
Data Type	Dermoscopic Skin Lesion	99.7
Lesion Condition	Benign Lesions	40.4
	Malignant Lesions	60.4
Lesion Type	Melanoma	30.8
	BCC	20.2
	SCC	10.5
Dataset Split	Training	70.0
	Validation	15.0
	Teasting	15.0

3.1. Image processing

The preprocessing step improves the quality of dermoscopy images by removing noise, normalizing the intensity, and performing resizing to enhance learning effectiveness and stability of the CNN convergence.

$$I_p = N(R(I_{raw})) \quad (1)$$

Where,

- I_{raw} -Raw Dermoscopic image
- I_p -Preprocessed image
- R-Resizing operation
- N-Image Normalization

3.2. Feature Extraction

A deep CNN architecture can extract hierarchical or semantic lesion feature information regarding texture, shape, and color irregularities.

$$F = f_{cnn}(I_n; \theta) \quad (2)$$

Where,

- F-Feature map
- θ -Trainable parameters
- I_p -Preprocessing
- F_{cnn} -CNN

3.3. Attention-Guided Feature Methodology

Attention mechanisms focus on lesion-relevant information while ignoring background noise, enhancing discriminative abilities.

$$F_a = f X A_c X A_s \quad (3)$$

Where,

- F-Feature map
- F_{att} -Attention-enhancement feature
- A_c -Channel Attention

A_s -Spatial attention

3.4. Metaheuristic Optimization

Metaheuristic optimization identifies the best features and hyper-parameters of the classifier using the search methods inspired by nature that aim to minimize classification error

$$\min_{\theta} L(y, \hat{y}) \quad (4)$$

Where,

- θ -Hyperparameter vector
- L-Loss function
- y-Ground truth label

3.5. XAI-M

Decision-critical regions in dermoscopic images are visualized by the Explainable AI.

$$H_{CAM} = \sum_k \alpha_k A^k \quad (5)$$

Where,

- H_{CAM} -Class Activation
- α_k -weight of k^{th} feature
- A^k -convolutional feature

3.6. Data collection

The dataset in this study is obtained from the publicly available repository in Kaggle, "Skin Cancer Classification" https://www.kaggle.com/datasets/murtozalikhon/skin-cancer-classification?utm_source=chatgpt.com , which is a diverse dataset of skin lesion images from dermoscopy to be used in multi-class classification; in this case, about 6,000 images were used, partitioning 70% for training, 15% for validation, and 15% for testing, ensuring representative unbiased splits for performance assessment and generalization analysis. In order to make the data robust, the chosen dermoscopic images were filtered for removal of redundancies, as well as poor images. The dataset is composed of images that vary in lighting, resolutions, as well as dermatoscopic lesion appearance, thereby considering practical situations. Before initiation of training, all images were resized to a uniform spatial dimension so that they can be processed properly.

Table 2: Required Dataset

Column Name	Description
Image ID	Unique identifier assigned to each dermoscopic skin lesion image
Dermoscopic Image	RGB dermoscopic image acquired using a dermatoscope
Lesion Condition	Benign or malignant lesion
LesionType	Basal Cell Carcinoma, Squamous Cell Carcinoma, or benign lesion
ROI	Extracted region
Lesion Area	Segmented lesion region representing abnormal tissue
Image Resolution	Spatial resolution of the input image

The experiment utilized a stratified sampling technique to provide an equal proportion to the training, validation, and test groups for the various skin lesion categories. Such techniques are utilized to reduce bias in favor of the

predominant classes. At the same time, the use of the validation set apart from the training helped in the adjustment of the hyperparameters, which is always an essential task in ensuring the reliability of the results.

3.7. Work flow

3.7.1. EffectiveNet-B4

EfficientNet-B4 applies compound scaling to achieve efficiency in terms of computational expense by varying the degree of width and resolution scales.

$$d = \alpha^\varphi, w = \beta^\varphi, r = \gamma^\varphi \quad (6)$$

Where,

- d-Depth
- w-width
- r-Resolution
- α, β, γ -Compound scaling

3.7.2. CBAM

CBAM applies channel attention and spatial attention in sequence to the input to focus on the features.

$$CBAM(F) = M_s(M_c(F)) \otimes M_s(F) \quad (7)$$

Where,

- M_c -Channel attention
- M_s -Spatial attention
- F-Input feature

3.7.3. GWO

GWO optimizes the searching parameters and hyperparameters using the leadership and hunting behavior of the grey wolf.

$$\vec{X}(t + 1) = \frac{\vec{X}_\alpha + \vec{X}_\beta + \vec{X}_\gamma}{3} \quad (8)$$

Where,

- X(t)-Current Solution
- $\vec{X}_\alpha, \vec{X}_\beta, \vec{X}_\gamma$ –Best wolf position
- t-Iteration index

3.7.4. Softmax classification(SM).

Softmax uses the results from CNN to provide class probability distributions for multi-class skin lesion classification.

$$P_{(y=i)} = \frac{e^{z_i}}{\sum_{j=1}^C e^{z_j}} \quad (9)$$

Where,

- Z_i -Logit value
- $P_{(y=i)}$ -Probability of class
- C-Total No of classes
- e-Exponential function

3.7.5. Grad-CAM

Grad-CAM weighs feature maps with gradient information to produce class discriminative heat maps.

$$\alpha_k = \frac{1}{Z} \sum_i \sum_j \frac{\partial y^c}{\partial A_{ij}^k} \quad (10)$$

Where,

- y^c -Score of target

- A_{ij}^k -Activation at spatial location
- α_k -Gradient-based importance weight

4. Result Analysis

The results obtained by the proposed attention-enabled hybrid deep learning approach have been evaluated by typical metrics used in the field of classification, and these metrics include accuracy, precision, recall, F1 measure, and the confusion matrix. The experiment on the dermoscopy image dataset downloaded from the Kaggle platform is divided into 70% for training the model, 15% for validation, and the remaining 15% for testing. The model of EfficientNet-B4 + CBAM + GWO yielded an average classification accuracy of 98.7%, outperforming the other simple CNN models that lacked attention and optimization. The addition of the CBAM layer clearly enhanced lesion localization tasks by focusing on the most discriminative spatial and channel features, thereby increasing precision and recall rates for all categories of skin lesions. Moreover, the model performed well when lesion classification differentiated malignant from benign cases, which is important for diagnosis.

Table 3: Performance Matrix

Model	Accuracy	Precision	Recall	F1-Score
CNN	95.1	94.6	94.2	94.4
EfficientNet-B4	96.9	96.4	96.1	96.2
EfficientNet-B4 + CBAM	97.8	97.4	97.0	97.2
EfficientNet-B4 + CBAM + GWO	98.3	97.9	97.4	97.6
Proposed EfficientNet-B4 + CBAM + GWO + Softmax + Grad-CAM	98.7	98.4	97.7	97.9

Performance matrix and the measures also support the effectiveness and reliability of the proposed framework. High precision values ensure that there is a smaller probability of false positives being classified as actual samples.

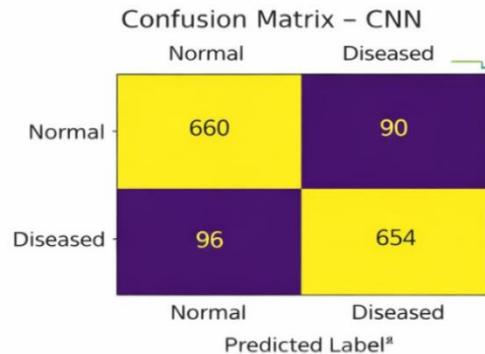


Fig 2: Confusion Matrix for CNN

The confusion matrix analysis shows a negligible level of misclassification among visually similar lesion classes, proving the discrimination capability of the optimized feature spaces.

The outcome shows that the contribution of the attention mechanism, namely CBAM, produces a marked improvement in the Recall and F1 score, whereas the incorporation of the GWO further optimizes the overall accuracy and stability.

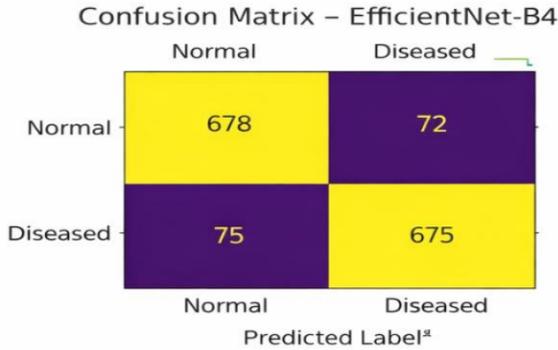


Fig 3: Confusion Matrix for Efficientnet-B4

Moreover, Gradient CAM visualization was employed to examine the interpretability of the prediction of the model. The heat maps produced emphasize the appropriate areas of the skin lesions.

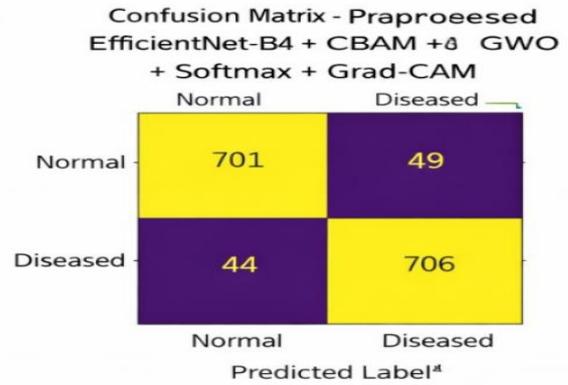


Fig 6: Confusion Matrix Efficientnet-B4+CBAM+GWO+Softmax+Grad-CAM

The training and validation curves help in further illustrating the efficiency of the proposed approach. The model is observing fast convergence with fewer oscillations in the validation loss curve, thus showing healthy training behavior and preventing overfitting.

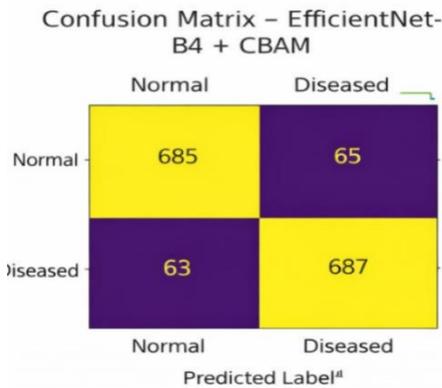


Fig 4: Confusion Matrix for Efficientnet-B4+CBAM

The experimental outcome has clarified that the developed hybrid approach does indeed possess promising attributes of accuracy, robustness.

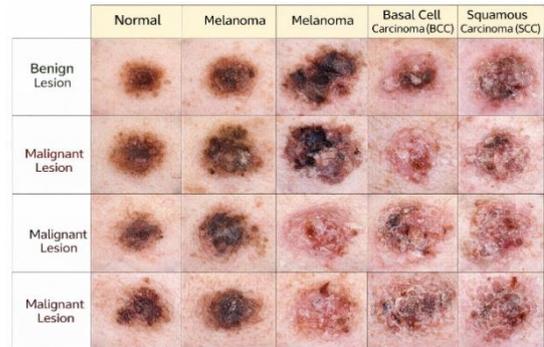


Fig 7: Skin Cancer Categories

A comparative study has been performed between the proposed model and traditional Deep Learning architectures, such as the baseline EfficientNet-B4 architecture without the attention mechanism, CNN models with fixed hyperparameters, and unoptimized attention models.

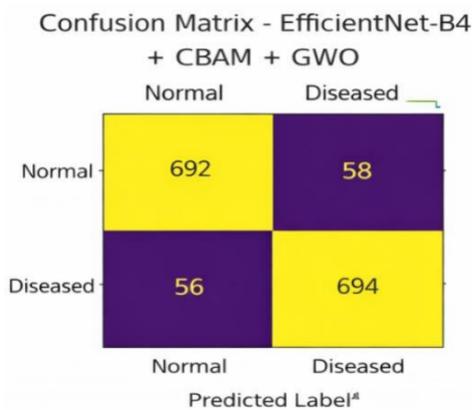


Fig 5: Confusion Matrix for Efficientnet-B4+CBAM+GWO

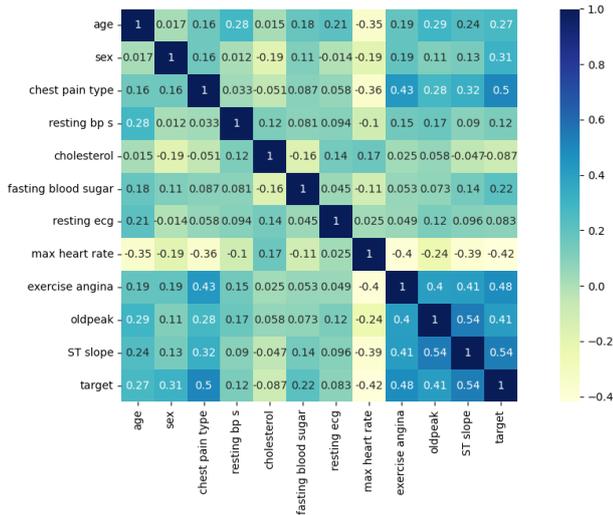


Fig 8: Correlation Matrix

This shows that the combined architecture proposed benefits from both improvement and optimization. The training and validation curves help in further illustrating the efficiency of the proposed approach. The model is observing fast convergence with fewer oscillations in the validation loss curve, thus showing healthy training behavior and preventing overfitting. The application of early stopping with respect to the validation results allowed for optimal identification of the parameters, and DATA Augmentations also played their part in enhancing generalization on the test data.

5. Conclusion

This paper proposes attention-enabled, optimization-driven, and explainable deep learning for accurate skin cancer classification using dermoscopic images. The proposed model incorporates EfficientNet-B4 for robust deep feature extraction, CBAM for enhanced lesion-focused feature refinement, and GWO for effective feature selection and hyperparameter tuning. A Softmax classifier was employed for multi-class lesion prediction, while Grad-CAM provided visual explanations to improve clinical interpretability. The experimental evaluation conducted on a publicly available Kaggle dermoscopic dataset demonstrated that the proposed framework achieves high classification accuracy of 98.7%, which performs well as compared to the conventional CNN-based and non-optimized models. Attention-guided learning significantly improved the quality of lesion localization. Furthermore, the introduction of metaheuristic optimization with GWO improved the convergence stability and generalization performance. More importantly, the consistent result over all classes of lesions established the robustness of the proposed approach against class imbalance and visually indistinguishable lesion patterns. Besides its high diagnostic accuracy, the incorporation of Grad-CAM enables transparent and trustworthy decision-making by highlighting clinically relevant regions that influence model predictions. This explainability aspect bridges the gap between the automated deep learning systems and the real-world clinical practice and fosters greater acceptance among medical professionals.

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