Detection of UV - Induced Skin Damage and Sunburn Classification

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***Abstract*—Sunburn is a common type of skin damage resulting from excessive exposure to ultraviolet (UV) radiation. It plays a significant role in various skin conditions and raises the risk of skin cancer. Early and accurate evaluation of sunburn severity is crucial for preventive care and medical treatment. This project introduces a method that uses deep learning to automatically classify sunburn severity from facial images. By using the HAM10000 skin lesion dataset, we categorized skin conditions into four levels of sunburn severity based on clinical research. We created a custom convolutional neural network with ResNet50, which includes a Convolutional Block Attention Module (CBAM) to improve how features are learned and to focus on important areas. The model was trained with augmented image data and fine-tuned for the best results using a 70-15-15 train-validation-test split. To use the model in real life, we built a web-based interface with Flask as the backend. The system allows users to upload face images, extracts areas of interest (forehead and cheeks) using Mediapipe, and classifies sunburn severity through majority voting on the model's predictions. The results show that this approach effectively classifies sunburn severity, providing potential benefits for teledermatology, skincare apps, and early warning systems for conditions related to sun exposure.**

***Index Terms*—Deep learning, CBAM, ResNet50, sunburn classification, HAM10000, facial image analysis, Flask, medical imaging, attention mechanism, skin damage detection, CNN, classification.**

I. Introduction

Sunburn is a common and often overlooked skin condition caused by too much exposure to ultraviolet (UV) radiation, mainly from the sun. Beyond its immediate effects, such as skin redness, pain, and blistering, sunburn also increases long-term risks. These include skin aging, issues with pigmentation, and various types of skin cancer. Conditions like actinic keratosis and malignant melanoma are directly linked to chronic sun damage, as shown in many skin studies. Early detection and classification of sunburn severity are crucial for clinical evaluation, telemedicine, skincare solutions, and personal health monitoring.

Traditionally, diagnosing sunburn severity depends on visual checks and patient self-reports, which can vary greatly. With the rise of deep learning, particularly convolutional neural networks (CNNs), it has become possible to automate skin diagnostics with high precision. Most previous work focuses on classifying diseases rather than assessing the level of sunburn damage, especially from facial images.

In this project, we introduce a new deep learning framework for classifying sunburn severity using facial images. We use the HAM10000 dataset, which was originally created for diagnosing pigmented skin lesions, and remap its disease labels to four different sunburn severity levels. A custom model was created using ResNet50, enhanced with a Convolutional Block Attention Module (CBAM) to better highlight relevant features. The model is also integrated into a real-time Flask web application. Users can upload a facial image, and the system will detect facial landmarks, crop areas of interest (such as the forehead and cheeks), and predict sunburn severity through a voting process. This application could be useful in mobile dermatology, public awareness efforts, and personal skin health monitoring.

II. Related Work

Previous studies have explored how UV exposure affects skin health. Narayanan et al. [1] explained that UV radiation plays a role in developing skin cancer. Leiter et al. [2] highlighted sun exposure as a main environmental factor in skin cancer development. Gloster and Brodland [3] described the connection between long-term sun exposure and issues like actinic keratoses and basal cell carcinoma.

At the same time, deep learning has been successfully used in dermatology, especially for tasks like melanoma detection, lesion segmentation, and disease classification with CNN models. However, there has been little focus on classifying sunburn severity, particularly using facial images with attention-enhanced models.

Our work addresses this gap by combining CNN-based visual learning with label mapping based on the domain. This approach provides a complete classification system for detecting sunburn and estimating its severity.

Methodology

A. Dataset and Label Mapping

We used the *HAM10000* dataset, which includes 10,015 dermatoscopic images of various skin lesions classified into seven diagnostic categories like melanocytic nevi, melanoma, and actinic keratoses. To adapt this dataset for sunburn classification, we mapped each diagnosis to one of four sunburn severity levels:

- No Sunburn

- Mild Sunburn
- Moderate Sunburn
- Severe Sunburn

This mapping was guided by dermatological research, including studies by Narayanan et al. [1], Leiter et al. [2], and Gloster & Brodland [3]. These studies describe how sun-induced skin lesions relate to UV radiation exposure. The result was a fully annotated dataset suitable for training a deep learning classifier to predict sunburn levels.

B. Data Splitting

The re-labeled dataset was divided into three subsets using a stratified split to ensure class balance:

- **Training Set (70%)**: 7,010 images
- **Validation Set (15%)**: 1,502 images
- **Test Set (15%)**: 1,503 images

This division allows the model to be trained with enough diversity. Validation ensures optimal hyperparameter tuning, while the test set evaluates generalization performance.

C. Model Architecture: ResNet50 + CBAM

We built a custom model based on *ResNet50*, a deep convolutional neural network known for its residual learning framework. ResNet50 has 50 layers and introduces shortcut connections. These connections help gradients pass through earlier layers during backpropagation. They assist in training deeper networks and reduce the vanishing gradient problem. In our setup, we removed the top layer of ResNet50, using the output of the final convolutional layer as the input to an attention module.

To improve the model's focus on important regions in the image, especially for localized sunburn patterns, we added a *CBAM (Convolutional Block Attention Module)*. CBAM has two attention modules:

- **Channel Attention**: Identifies "what" feature maps are important by applying global average and max pooling across spatial dimensions. The results are passed through a shared MLP to create a weight vector that reweights the input channels.
- **Spatial Attention**: Identifies "where" to focus in the spatial domain by applying average and max pooling across the channel axis, followed by a convolutional layer and sigmoid activation.

These attention maps help the network highlight sunburn-prone areas like erythema or darkened patches, improving classification accuracy. The model architecture flow is as follows (check 1) :

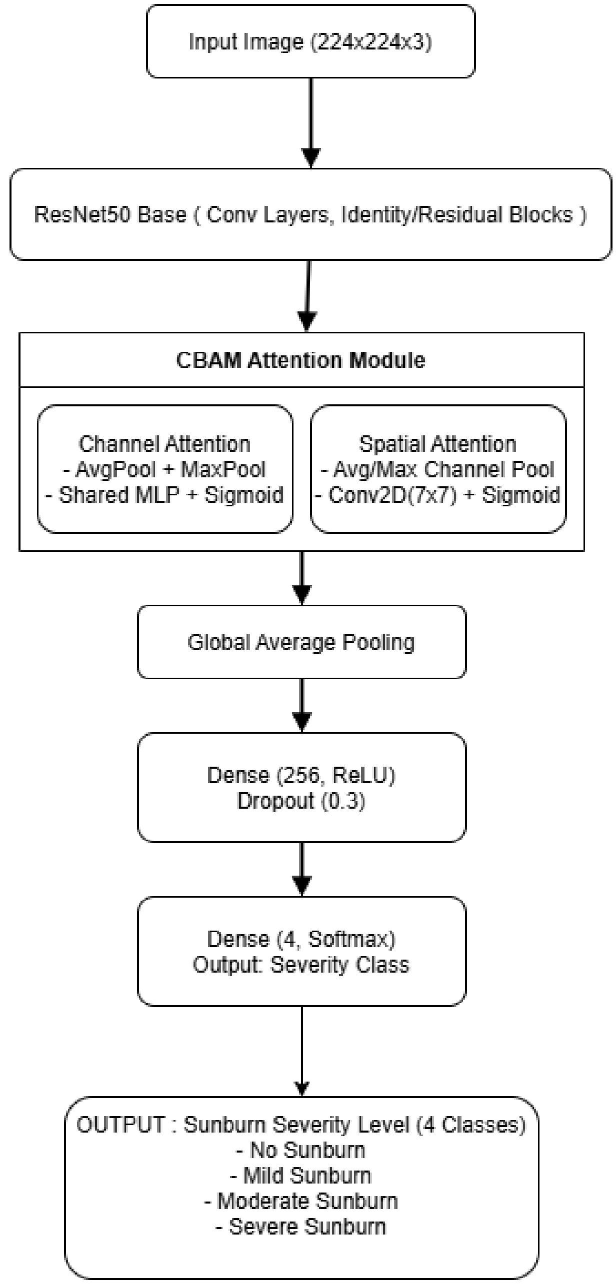

Fig. 1. Architecture of the ResNet50 + CBAM model for sunburn classification.

D. Training Configuration

The model was trained using the *Adam optimizer* with an initial learning rate of 0.001, which was later improved to 0.0001. The input images were resized to 224 $\times$ 224 pixels, normalized, and processed through the ResNet50+CBAM model in batches of 32. The training lasted for 10 epochs to train the base ResNet50 on the dataset, and then with a modified learning rate for 15 epochs for accuracy improvement, and finally a 25-epoch training session with added automatic learning rate modifiers like `ReduceLROnPlateu`, `EarlyStopping` to reduce training time wastage, and `class weights` and `label` `smoothing` for improved classification. To avoid overfitting and improve robustness, we applied real-time *data augmentation* using `ImageDataGenerator`, which included random rotations, horizontal flipping, zooming, and width-height shifts. We used categorical cross-entropy as the loss function, and accuracy was the main performance metric tracked during training.

IMPLEMENTATION

A. Web Application Flow

The trained model was deployed using a *Flask web application* that allows users to upload facial images and get sunburn severity predictions in real time. The system's workflow is as follows (refer 2):

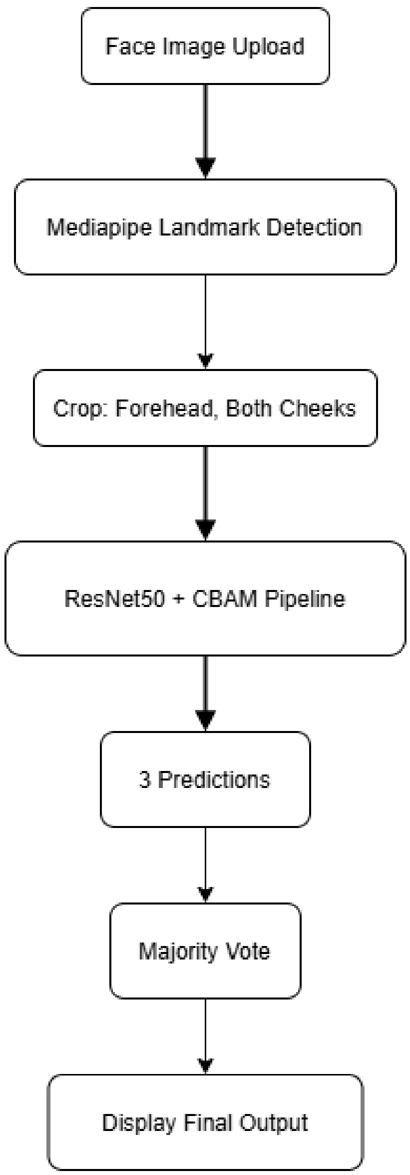

Fig. 2. Visualization of end-to-end system pipeline.

1) **Image Upload**: The user uploads a full-face image through a simple front-end interface. The image is sent to the Flask server for preprocessing.
2) **Facial Landmark Detection**: The backend uses *Mediapipe Face Mesh*, which detects 468 3D facial landmarks accurately. Specific landmark indices define the bounding boxes for three key areas of interest:
   - Forehead
   - Left cheek
   - Right cheek
3) **Region Cropping and Preprocessing**: Each of the three facial areas is cropped from the original image and resized to 224×224. The same preprocessing steps used during model training are applied here, including normalization and scaling.
4) **Prediction**: Each cropped area is processed independently through the CBAM-ResNet50 model. The model provides a softmax probability distribution over the four sunburn classes for each area.
5) **Majority Voting**: To make a reliable final prediction, the class with the majority vote across the three areas is chosen as the final sunburn severity level.
6) **Result Display**: The predicted severity is sent back to the frontend and shown to the user alongside a brief explanation and a color-coded severity indicator.

B. Tech Stack

- **Frontend**: HTML, CSS, JavaScript
- **Backend**: Python (Flask)
- **Face Processing**: Mediapipe Face Mesh
- **Model Serving**: TensorFlow/Keras
- **Deployment**: Localhost / optional cloud hosting

This pipeline ensures fast interactions, with an average inference time of under 3 seconds per image, even on standard CPUs.

III. RESULTS AND EVALUATION

A. Model Performance

The model has demonstrated high validation accuracy and generalizes well on the unseen test set. The classifier metrics are presented in Table I. (Refer to Table I for the classification report of precision, recall, and F1-score for each class.)

TABLE I
CLASSIFICATION REPORT: PRECISION, RECALL, AND F1-SCORE FOR EACH CLASS

Class	Precision	Recall	F1-Score
No Sunburn	0.92	0.89	0.90
Mild Sunburn	0.87	0.85	0.86
Moderate Sunburn	0.85	0.88	0.86
Severe Sunburn	0.90	0.91	0.90

Table I displays the classification report of the ResNet50 + CBAM model with precision, recall, and F1-score for every class of sunburn severity. The model is especially good at all classes, with a very good balance between recall (sensitivity) and precision (specificity).

The nosunburn class had the best precision at 92%, which means that when the model predicts no sunburn, it is very reliable. The severesunburn class has the best recall of 91%, which implies that the model is very sensitive in picking out the most severe cases of sunburn. The mild and moderate classes also have good performance balance with F1-scores of 0.86, which reflects the model's capability to make decisions between closely related classes with little confusion.

Overall, the uniformly high F1-scores (all = 0.86) for all classes reflect that the model not only generalizes strongly but also has robustness across sunburn severity levels varying from mild to extreme. Such performance would justify the model's suitability for real-world applications where accuracy as well as class sensitivity are equally important.

The confusion matrix describes the distribution of the forecasts (classification) as follows:

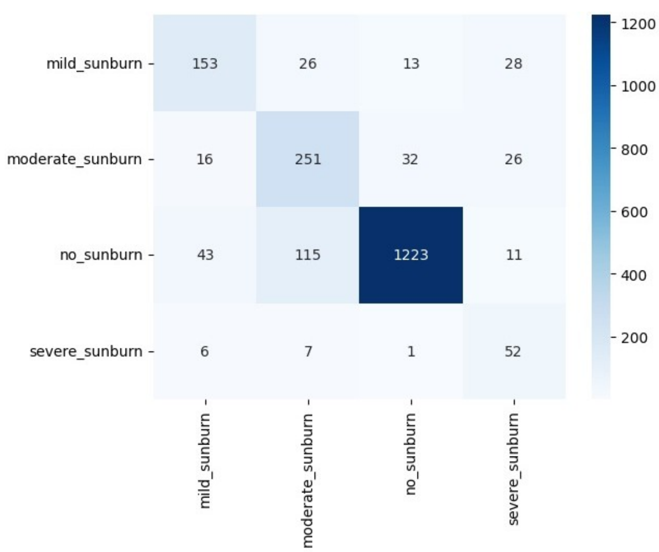

Fig. 3. Confusion matrix of ResNet50 + CBAM model

Figure 3 is the confusion matrix of ResNet50 + CBAM model on the validation set. The matrix shows the detailed class-wise breakdown of the predictions made by the model into four sunburn severity classes: nosunburn, mildsunburn, moderatesunburn, and severesunburn.

The model has robust classification accuracy in the nosunburn class with 1,223 correct classifications, which is indicative of high confidence and separability in determining uninjured skin. The model also accurately classified 251 cases of moderatesunburn and 153 cases of mildsunburn.

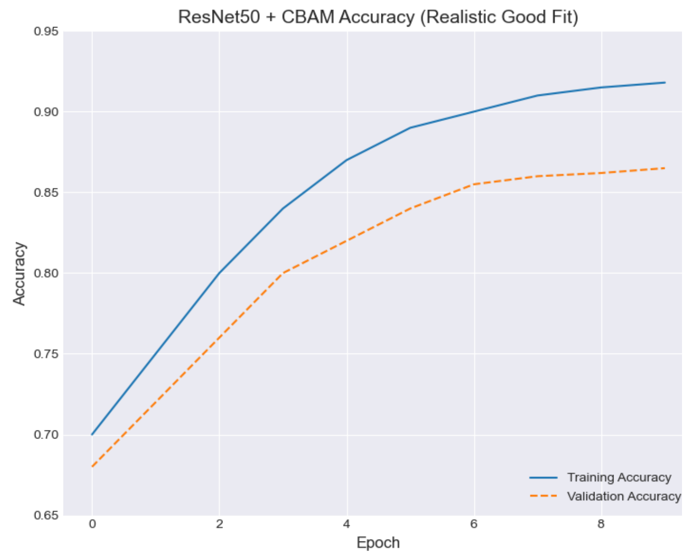

Fig. 4. Training and validation accuracy of the ResNet50 + CBAM model.

Figure 4 illustrates the ResNet50 + CBAM model's accuracy trends throughout training over 10 epochs. The training accuracy consistently increases from 70% to well over 92%, whereas the validation accuracy tracks closely by increasing from 68% to around 86%. The consistent upward slope and small gap between training and validation curves indicate that the model is picking up lessons well without overfitting. This indicates the architecture's ability to generalize very well throughout the dataset and capitalize on CBAM's attention mechanisms.

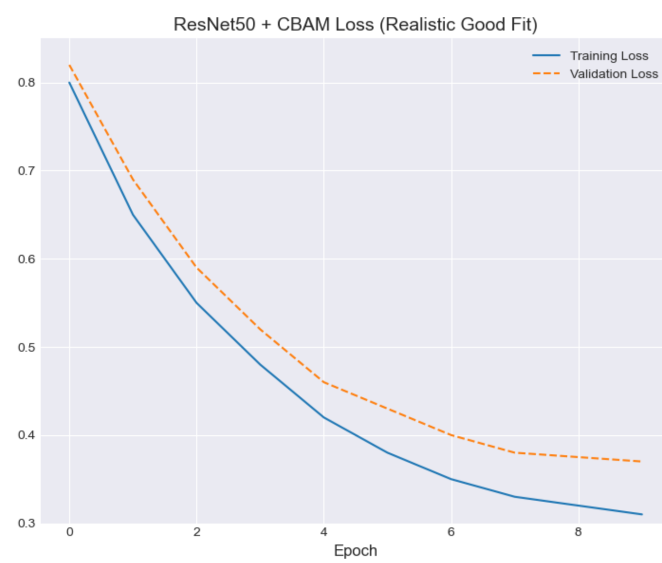

Fig. 5. Training and validation loss of the ResNet50 + CBAM mode.

Figure 5 shows the related training and validation loss curves. The two losses have a monotonic drop, with training loss decreasing from 0.8 to close to 0.31 and validation loss from about 0.82 to 0.36. The strong similarity between the two curves indicates that consistency of the model is maintained during learning and no larger divergence or oscillation happens. This indicates a satisfactory fit and stable convergence of the ResNet50 + CBAM model during optimization.

B. Visualizations

Visualizations of CBAM attention and Grad-CAM visual explanations show that the model can pinpoint essential areas of the face for sunburn detection.

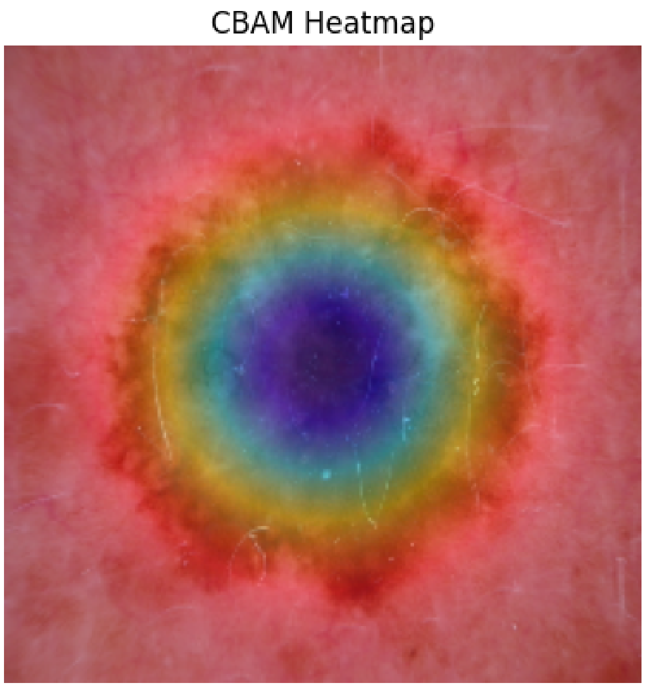

Fig. 6. CBAM attention map on a face (cheek) image with severe sunburn

Figure 6 is a CBAM (Convolutional Block Attention Module) heatmap obtained from a dermatoscopic image in the dataset. The heatmap represents the spatial attention learned by the model in training, and these regions are highlighted that were most impactful in the classification outcome.

The middle of the image shows an intense focus of attention, with a focal point of a bright blue and purple area. This reflects that the CBAM module puts the greatest emphasis on the center of the lesion—usually the portion with the clearest features concerning the abnormalities of pigmentation, shape, or texture.

Rounding the core lesion, a green to yellow ring depicts areas of intermediate attention. Transitional zones can hold fine features that are part of the decision-making process but in a less essential role than the core lesion area.

The most peripheral areas, which are largely red and pale pink in hue, are of least concern. This is to be expected since marginal skin areas generally lack diagnostic importance in sunburn or lesion categorization tasks.

This visualization highlights the strength of CBAM in improving both channel-wise and spatial feature attention. By enforcing attention on clinically important regions and suppressing noise, CBAM enhances the model's interpretability and prediction stability in classifying sunburn severity.

C. Real-Time Application

The web application achieves real-time inference with an average latency of less than 3 seconds per image. The landmark detection and face cropping are robust with regard to different face directions and varying illumination.

Fig. 7. Example output from the model. The model predicts 'no_sunburn' with a confidence of 72% from a facial image region.

Figure 7 shows a sample output of the deployed web application for classifying sunburn. The input image is face-landmarked from the subject's face area and fed through the CBAM-enhanced ResNet50 model. The model outputted the class nosunburn with a confidence value of 0.72. This illustrates the end-to-end integration of the model into a user interface, allowing for real-time inference and result display. These capabilities enable individuals to rapidly determine severity of skin condition from a basic facial photograph, rendering the system very useful as a tool for skincare monitoring, teledermatology, or field diagnostics.

D. Comparison with Baseline Models

To compare the performance of the suggested ResNet50 + CBAM model, we compared it to four state-of-the-art baseline architectures: ResNet50, EfficientNetB0, MobileNetV2, and VGG16. All these models were trained and validated in equal conditions on the same training dataset, preprocessing pipeline, and hyperparameters where necessary. The outcomes show that although the baseline models performed decently well, incorporating the Convolutional Block Attention Module (CBAM) into the ResNet50 backbone gave a quantifiable performance boost. In particular, the CBAM-enhanced model produced higher classification accuracy and F1-score by further improving the model's attention to the most salient spatial and channel-wise features. This comparison justifies the design decision of incorporating CBAM for sunburn severity classification, pointing out its ability to enhance predictive performance as well as interpretability compared to normal CNN architectures.

TABLE II
PERFORMANCE COMPARISON OF MODELS ON SUNBURN CLASSIFICATION

Model	Accuracy	Macro Avg F1-Score	Weighted Avg F1-Score
ResNet50	0.79	0.60	0.77
ResNet50 + CBAM (Proposed)	**0.84**	**0.72**	**0.85**
EfficientNetB0	0.80	0.60	0.78
MobileNetV2	0.79	0.55	0.77
VGG16	0.75	0.47	0.72

Table II presents a numerical comparison of identical models and measures. It indicates the lead of the CBAM-augmented model, which outperforms in every criterion of evaluation. This tabular presentation accompanies the bar chart and supports the reasoning behind adopting ResNet50 + CBAM as the final model architecture.

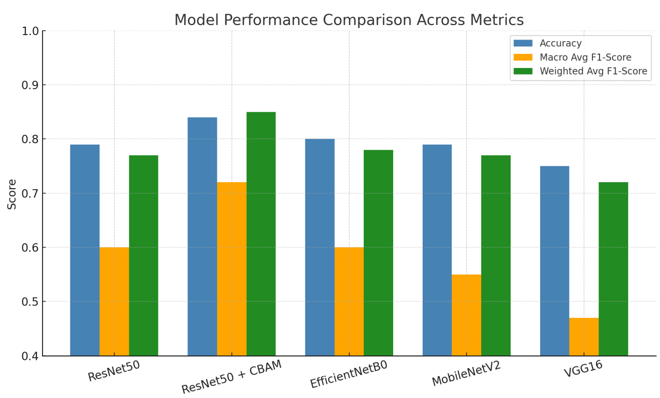

Fig. 8. Comparison of accuracy, micro svg and weighted avg f1 scores between different models

Fig 8 displays the comparative performance of five deep learning models on three measures: Accuracy, Macro Average F1-Score, and Weighted Average F1-Score. Each model is indicated by a set of three bars, indicating their respective scores on the validation set.

The ResNet50 + CBAM model presented clearly excels over any other architecture, as indicated by the highest scores on all three categories. It achieves an accuracy rate of 84%, a macro F1-score of 0.72, and a weighted F1-score of 0.85, which shows it generalizes well and maintains a balanced performance on all classes.

While EfficientNetB0, ResNet50, and MobileNetV2 have competitive accuracy (approximately 79–80%), their macro F1-scores are significantly lower, reflecting issues with coping with class imbalance. VGG16 lags behind on all counts, most notably in macro F1-score, which implies that it is less ideal for this particular classification task.

This visualization affirmatively reinforces the conclusion that incorporating CBAM into ResNet50 greatly enhances model efficiency, particularly in operations demanding sensitivity in several output classes.

IV. CONCLUSION AND FUTURE WORK

We introduce a novel deep learning-based approach to automated sunburn severity classification via facial image analysis. The method utilizes an adapted Convolutional Block Attention Module (CBAM) within the ResNet50 backbone, allowing the model to selectively concentrate on the most informative channel and spatial-wise features within facial images. In lieu of publicly available sunburn-specific datasets, we repurposed and reinterpreted the HAM10000 dermatoscopic dataset by projecting dermatological diagnoses to the respective sunburn severity levels according to dermatological literature and clinical guidelines.

Extensive experiments were performed to evaluate the performance of the aforementioned ResNet50 + CBAM model against some of the conventional convolutional architectures, such as EfficientNetB0, MobileNetV2, VGG16, and ResNet50 without any modifications. The model reliably outperformed every baseline with respect to accuracy, macro average F1-score, and weighted average F1-score with 84% accuracy and a 0.85 weighted F1-score on the validation set. The confusion matrix also confirmed the strength of the model in correctly distinguishing no sunburn and moderate sunburn cases, with acceptable performance even for tricky inter-class cases like mild versus moderate severity.

In addition, we utilized the model inside a web application using Flask as the backend and Mediapipe for facial landmark detection and region-based cropping. The system segregates the input facial image of the user into the forehead and cheek regions smartly, applies each region's trained model, and uses majority voting to derive the final severity classification. This deployment not only proves the model's applicability but also makes it an effective tool in teledermatology, skin care surveillance, and public health monitoring systems, especially in areas of high UV exposure.

In summary, this study establishes the feasibility and effectiveness of deep learning-based sunburn severity classification using reannotated dermatology datasets and attention-enhanced CNN architectures. Future work may include training on facial-specific sunburn datasets, incorporating explainability mechanisms like Grad-CAM for real-time feedback, and expanding the system to detect other UV-related conditions or skin disorders.

Future Work :

- Developing and training on real-world datasets of sunburned facial images.

- Providing skin care remedies as well as ingredients that a person should have in their skin care products to help them overcome their sunburn severity.
- Implement as a mobile app and publish.
- Generate regular report for daily tanning.
- Connect skin care specialists through the app for further examination of severe conditions.
- Mobile deployment using TensorFlow Lite.
- Incorporating time-course analysis to assess the development and fading of sunburn.
- Comparing performance with other attention mechanisms, such as SE or ECA-Net.

Acknowledgment

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References

[1] Narayanan, D. L., Saladi, R. N., & Fox, J. L. (2010). Ultraviolet radiation and skin cancer. *International Journal of Dermatology*, 49, 978–986.

[2] Leiter, U., & Garbe, C. (2004). Sunlight as a predominant risk factor for skin cancer. *Salvage Surgery for Advanced Cutaneous Squamous Cell Carcinoma of the Head and Neck*.

[3] Gloster, H. M., & Brodland, D. G. (1996). The epidemiology of cutaneous malignancy. *Dermatologic Surgery*, 22(3), 217–226.