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An Innovative CBR-Enhanced Approach for Skin Cancer Classification using Cascade Forest Model and Convolutional Neural Network with Attention Mechanism

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Abstract

INTRODUCTION: In recent years, skin cancer has emerged as a pressing concern, necessitating advanced diagnostic and classification techniques.
OBJECTIVES: This paper introduces an innovative hybrid approach that combines deep learning and machine learning to enhance the retrieval phase of the Case-Based Reasoning (CBR) system for skin cancer classification.
METHODS: The proposed approach leverages a Convolutional Neural Network (CNN) with an attention mechanism for feature extraction, which is used to build the case base. Additionally, it uses a modified cascade forest model, augmented with traditional machine learning classifiers for classification. This modified cascade forest model incorporates the XGBoost model in its initial layer to facilitate more effective ensemble learning and bolster predictive performance. Subsequently, in the following layers, it uses the Random Forest model to capitalize on its ability to handle high-dimensional feature spaces and maintain diversity within the ensemble.
RESULTS: Rigorous experimentation on the balanced HAM10000 dermoscopic image dataset, employing the Synthetic Minority Oversampling Technique (SMOTE), demonstrates the superiority of the modified cascade forest model in multi-class skin cancer classification. This model consistently achieves the highest metrics, including accuracy (95.40%), precision (95.49%), F1-Score (95.38%), and recall (95.44%).
CONCLUSION: This research highlights the efficacy of the proposed model compared to other classifiers, emphasizing the significance of the modified cascade forest model in enhancing the accuracy and reliability of skin cancer classification.

Keywords: skin cancer classification, case-based reasoning (CBR), retrieval phase, convolutional neural network (CNN), cascade forest model, attention mechanism, SMOTE technique.

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1. Introduction

Skin cancer is a significant global health concern (Gasmi, Djebbar et al. 2024), with its incidence rising at an alarming rate (Zhang, Cai et al. 2020). This increase has emphasized the urgent need for advanced techniques that ensure accurate diagnosis and classification of skin cancer (Kumar, Suganthi et al. 2022).
Despite notable advancements in artificial intelligence (AI) and non-invasive imaging technologies like dermoscopy, existing approaches for automatic dermoscopic skin cancer

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classification face challenges related to generalization and achieving satisfactory classification results (Thurnhofer-Hemsi and Domínguez 2021). While AI and machine learning have shown remarkable promise in various medical domains, the nuances of skin cancer classification present unique obstacles (Gasmi, Djebbar et al. 2022). These include variations in skin types, lesion appearances, and the subtle differences between benign and malignant growths.

Accurate and reliable classification of skin cancer is crucial for early detection and appropriate treatment. In medical practice, healthcare professionals often encounter difficulties in distinguishing between different types of skin cancer, particularly those with similar characteristics, making it a complex task (Vestergaard, Macaskill et al. 2008). The subtle visual disparities between skin lesions pose a significant challenge, even for experienced dermatologists. As a result, there is a pressing need to explore innovative approaches that enhance the accuracy and effectiveness of skin cancer classification systems. These solutions can provide invaluable support to medical professionals in making informed decisions regarding patient care and treatment options (Gasmi, Djebbar et al. 2022).

In response to these multifaceted challenges, this research article introduces a groundbreaking hybrid approach that seamlessly integrates deep learning and machine learning methodologies. This unique approach represents a pivotal step in addressing the evolving landscape of skin cancer diagnosis and classification. The proposed method is designed to enhance the retrieval phase of the Case-Based Reasoning (CBR) system (Gasmi, Djebbar et al. 2022) for skin cancer classification. By leveraging the power of convolutional neural networks (CNNs) with an attention mechanism, the proposed method facilitates effective feature extraction from dermoscopic images, enabling a more comprehensive visualization of skin disorders. It is essential to harness cutting-edge technologies like deep learning to discern patterns and details that may escape the human eye, ultimately contributing to more accurate diagnoses (Gasmi, Djebbar et al.).

Additionally, the proposed approach incorporates a modified cascade forest model, strategically augmented with traditional machine learning classifiers, to enable accurate classification of skin cancer. This fusion of advanced techniques enhances the performance of the retrieval phase of the CBR system, improving the overall accuracy and reliability of skin cancer classification.

To evaluate the effectiveness of the proposed approach comprehensively, a series of rigorous experiments are conducted on the balanced HAM10000 dermoscopic image dataset (Tschandl, Rosendahl et al. 2018). The Synthetic Minority Oversampling Technique (SMOTE) (Chawla, Bowyer et al. 2002) is employed to address class imbalance, ensuring a robust evaluation. The outcomes of these experiments provide invaluable insights into the potential of the proposed approach to revolutionize the landscape of skin cancer classification.

In summary, the main contributions of this research are as follows:

1. Introducing a novel hybrid approach that combines deep learning and machine learning methods to enhance the retrieval phase of the Case-Based Reasoning system for skin cancer classification.
2. Leveraging convolutional neural networks with an attention mechanism for effective feature extraction.
3. Employing a modified cascade forest model and classic machine learning models for accurate classification of skin cancer.

The remainder of this paper is organized as follows. Section 2 provides a summary of related work in the literature. Section 3 presents the proposed approach, detailing the dataset used, important preprocessing steps, the architecture of the CNN with attention mechanism for relevant feature extraction, and the modified cascade forest model. Section 4 illustrates the different performance measures computed. Section 5 discusses the experimental results. Finally, Section 6 concludes the paper, summarizing the findings and discussing potential avenues for future research.

2. Related Work

Several studies have been conducted to classify skin cancer using various Deep Learning (DL) and Machine Learning (ML) models, as well as various skin cancer datasets. Table 1 summarizes some of these studies.

In (Chaturvedi, Gupta et al. 2020), the MobileNet model, pre-trained on the ImageNet dataset, was employed for skin cancer classification. The authors evaluated their approach on the HAM10000 dataset, balanced through data augmentation technique. They achieved an overall accuracy of 83.1%.

In (Alam, Shaukat et al. 2022), the authors also utilized data augmentation to balance the unbalanced classes in the HAM10000 dataset. They implemented three models, namely AlexNet, InceptionV3, and RegNetY-320, for skin cancer detection and classification. Among these models, the RegNetY-320 model outperformed the others, achieving an accuracy of 91% and an F1-score of 88.1%.

Reddy (Reddy 2018) proposed a model based on the ResNet50 architecture to classify dermoscopy images of skin lesions into seven classes from the HAM10000 dataset. The model achieved an overall accuracy of 83.1%.

In (Pratiwi, Nurmaini et al. 2019), VGG-19 was employed as a CNN architecture, achieving an accuracy of 87.64% for classifying skin lesions as benign melanocytic nevi or malignant melanoma.

Polat and al. (Polat and Koc 2020) addressed the problem of multi-class classification of skin diseases using two different methods. The first method utilized a CNN model trained and tested on raw dermatological images from the HAM10000 dataset, achieving a classification accuracy of 77%. The second method combined seven different CNN models using the One-versus-All (OVA) approach, resulting in improved classification performance with an accuracy of 92.90%.

In (Thurnhofer-Hemsi and Dominguez 2020), five CNN models (DenseNet201, GoogLeNet, Inception-ResNetV2, InceptionV3, MobileNetV2) were fine-tuned using the HAM10000 dataset. The study proposed a simple model and a 2-level hierarchical model. DenseNet201 emerged as the best deep network, enabling the simple model to achieve 95% accuracy for binary classification and classification of the seven classes.

Chaturvedi and al. (Chaturvedi, Tembhurne et al. 2020) proposed a computer-assisted system for classifying multi-class skin cancers, combining various CNN models (InceptionV3, ResNeXt101, InceptionResNetV2, Xception, NASNetLarge). The ResNeXt101 and InceptionResNetV2 + ResNeXt101 models achieved maximum accuracies of 93.20% and 92.83%, respectively, for individual and ensemble models.

In 2021, (Shete, Rane et al. 2021) achieved a skin cancer classification accuracy of 90.51% using a CNN model and transfer learning with the ResNet model.

In (Ray 2018), the authors proposed a new method for classifying images of skin lesions. They utilized the ResNet50 model as the architecture for the convolutional neural network (CNN) to extract the characteristics of the skin lesion images. Subsequently, they employed the Deep Forest model to classify the extracted features. The authors achieved a training accuracy of 97.15% and a test accuracy of 80.04% on the ISIC 2018 dataset.

The authors in (Keerthana, Venugopal et al. 2023) aimed to develop an automated system for classifying skin lesions using two hybrid CNN models, namely DenseNet-201 and ResNet-50, in combination with an SVM classifier at the output layer. Their objective was to accurately classify dermoscopy images as either benign or melanoma lesions, utilizing the ISBI 2016 dataset. They achieved an impressive accuracy of 88.02% for skin lesion classification.

In (Pham, Luong et al. 2018), the authors proposed a melanoma classification system based on a hybrid approach that combines the CNN model Inception V4 with machine learning techniques such as Random Forest and other methods. To address the limited availability of labeled data in melanoma classification, they employed Data Augmentation (DAug) techniques to mitigate overfitting. The authors evaluated the performance of their hybrid model, Inception V4_Random Forest, using the 2017 ISBI Challenge dataset. The hybrid model achieved an accuracy of 88.7% with DAug-100, 88.5% with DAug-50, and 88.3% without DAug.

Table 1. Summary of Studies on DL and ML Applications in Skin Cancer Classification.

Paper	Model	Dataset	Accuracy
(Chaturvedi, Gupta et al. 2020)	MobileNet	HAM10000	83.1%
(Alam, Shaukat et al. 2022)	AlexNet, InceptionV3, RegNetY-320	HAM10000	91% (RegNetY-320)
(Reddy 2018)	ResNet50	HAM10000	83.1%
(Pratiwi, Nurmaini et al. 2019)	VGG-19	HAM10000	87.64% (binary classification)
(Polat and Koc 2020)	CNN (various models)	HAM10000	77% (method 1), 92.90% (method 2)
(Thurnhofer-Hemsi and Dominguez 2020)	DenseNet201, GoogLeNet, Inception-ResNetV2,InceptionV3, MobileNetV2	HAM10000	95% (binary classification), 95% (7-class classification)
(Chaturvedi, Tembhurne et al. 2020)	InceptionV3,ResNeXt101, InceptionResNetV2,Xception, NASNetLarge	HAM10000	93.20% (ResNeXt101), 92.83% (InceptionResNetV2+ ResNeXt101)
(Shete, Rane et al. 2021)	CNN (ResNet with transfer learning)	HAM10000	90.51%
(Ray 2018)	ResNet50, Deep Forest	ISIC 2018	80.04%
(Keerthana, Venugopal et al. 2023)	DenseNet-201, ResNet-50, SVM	ISBI 2016	88.02% (binary classification)
(Pham, Luong et al. 2018)	Inception V4, Random Forest	2017 ISBI Challenge	88.7% (DAug-100), 88.5% (DAug-50), 88.3% (without DAug)

Based on previous research in skin cancer classification, several studies have utilized DL and ML models to achieve promising outcomes. These models, including MobileNet, AlexNet, InceptionV3, ResNet50, VGG-19, and DenseNet201, have been applied to extract features from skin cancer datasets like HAM10000 and ISIC 2018, exhibiting high accuracy in categorizing skin lesions.
However, a limitation observed in some of these studies is the reliance on either a single model or a combination of models without considering the significance of specific features. In our approach, we aim to overcome this limitation by introducing a novel CNN model integrated with an attention mechanism and a modified cascade deep forest.

3. Materials and Methods

This section provides a detailed explanation of the steps involved in the suggested methodology, starting from the dataset description of skin cancer images and leading up to the classification of these images. A comprehensive flowchart of the suggested approach is presented in Figure 1. As depicted in Figure 1, the first step is the pre-processing phase, which aims to balance and normalize the images dataset. Following the pre-processing step, the suggested CNN model is trained to extract relevant features from both the original unbalanced HAM10000 dataset and the original balanced HAM_SM dataset. Once the features are extracted, the initial case base of the CBR model is established to train the classifiers. These classifiers are then tested using the test case base. Each step of the suggested architecture is explained in detail in the following subsections.

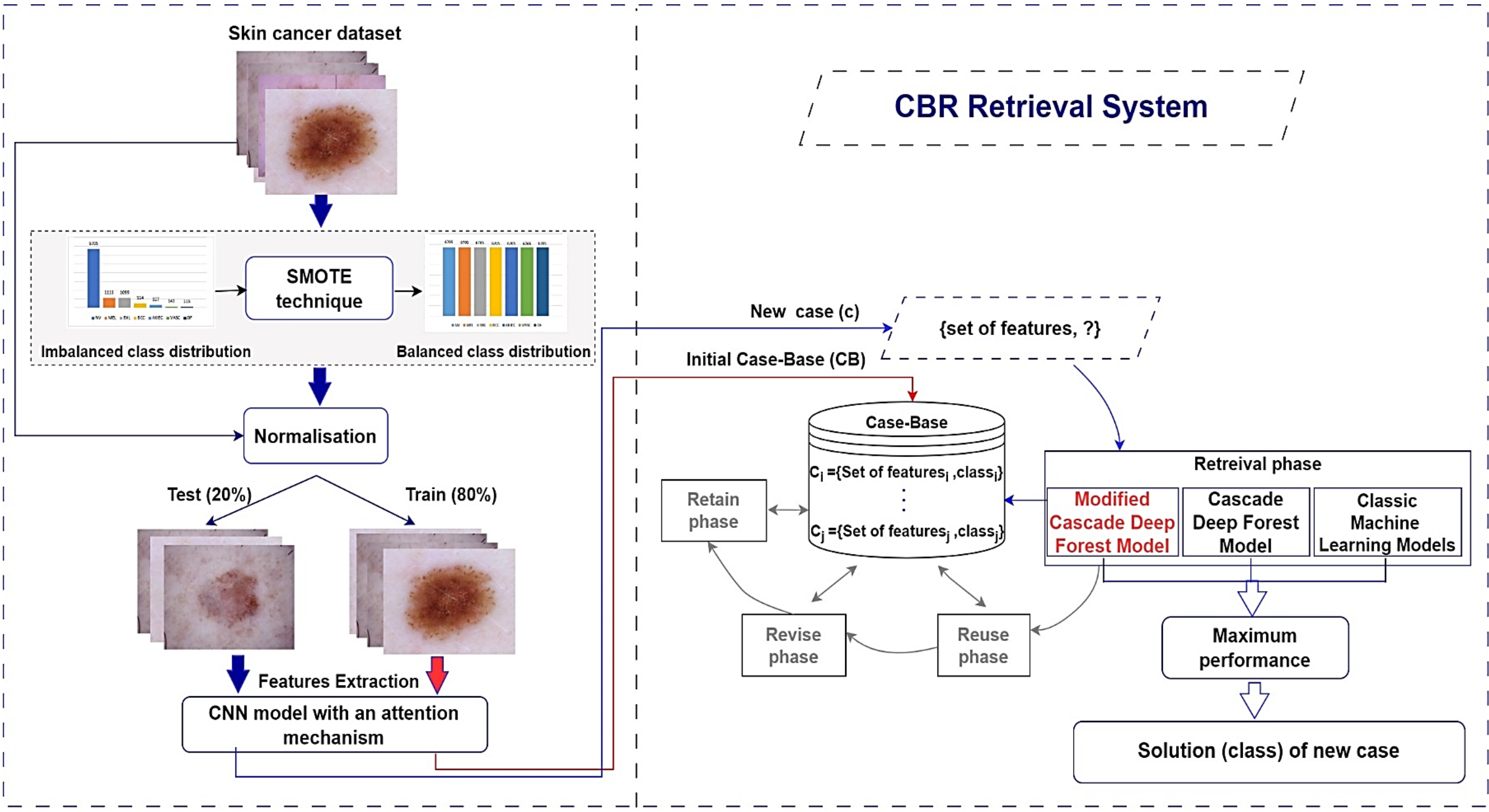

Figure 1. Diagram of the suggested framework for the multi-class skin cancer classification.

3.1. Dataset and preprocessing

In our work, we selected the HAM10000 dataset (Tschandl, Rosendahl et al. 2018) of skin lesion images (Figure 3) for skin cancer classification. This unbalanced dataset requires pre-processing before being used. As it is illustrated in Figure 2 (A), the images belonging to the Melanocytic nevus (NV) class represent more than half of the dataset, which may influence the classification performance of the other minority classes. Detailed information regarding the class distribution of this dataset can be found in Table 2.

Table 2. The description of the HAM10000 dataset.

Dataset name	Description	Class
HAM10000	10,015 images image size: (28, 28, 3)	0: Melanocytic nevus (NV, 6,705 images) 1: Melanoma (MEL, 1,113 images) 2: Benign keratosis (BKL, 1,099 images) 3: Basal cell carcinoma (BCC, 514 images) 4: Actinic keratoses (AKIEC, 327 images) 5: Vascular lesion (VASC, 142 images) 6: Dermatofibroma (DF, 115 images)

To overcome this problem, we applied the Synthetic Minority Oversampling Technique (SMOTE) (Chawla, Bowyer et al. 2002), which deals with unbalanced datasets by generating synthetic data for the minority class. Instead of simply duplicating existing samples, SMOTE performs specific operations on the minority class samples, using the K nearest neighbors (KNN) of the samples examined [41]. The following describes the sequential steps involved in the SMOTE algorithm (Algorithm 1):

Algorithm 1: SMOTE algorithm (Chawla, Bowyer et al. 2002)

Input: Imbalanced dataset HAM10000,
Output: Balanced dataset HAM_SM,
Begin
1.Identify the minority class in the imbalanced dataset.
2.Determine the desired number of synthetic samples to be generated for the minority class.
3.For each sample x_i in the minority class:
a. Find its k nearest neighbors (KNN) using a distance metric (Euclidean distance).
4.Randomly select k nearest neighbors for each minority class sample x_i.
5.For each selected nearest neighbor x_j:
a. Generate a random number (α) between 0 and 1.
b. Compute the difference between the feature vectors of the minority sample x_i and the selected nearest neighbor x_j.
c. Multiply the difference by α.
d. Add the result to the feature vector of the minority sample to create a new synthetic (new_syn) sample using the interpolation formula: $x_{new\_syn} = x_i + (x_i - x_j) \times \alpha$.
Repeat steps 3-5 for the desired number of synthetic samples to be generated.
End.

After resampling the HAM10000 dataset using the SMOTE technique, we obtained a dataset of 46,935 skin lesion images (HAM-SM), with a balanced distribution between the seven classes (Fig.2 (B)). We then normalized the images by dividing them by 255, in order to reduce computational complexity in the feature extraction phase using the suggested CNN model. After normalization, the pixel range of each image in the HAM-SM dataset will be 0 to 1 instead of 0 to 256. Finally, we split the HAM-SM dataset into 80% for training and 20% for testing using the Random Split technique.

3.2. CNN-based feature extraction with attention mechanism

In this research, we propose a Convolutional Neural Network (CNN) architecture with an attention mechanism for accurate classification of skin cancer types. The model, as depicted in Figure 4, is specifically designed to effectively extract discriminative features from the balanced HAM-SM dataset. It begins with convolutional layers that perform robust feature extraction, followed by MaxPooling2D layers for downsampling while preserving essential information. The key innovation lies in the incorporation of an attention mechanism, which enables the model to selectively focus on relevant regions within the feature maps. This attention mechanism is achieved through the utilization of several layers:

First, attention weights are computed using a Dense layer with softmax activation. These attention weights represent the importance of different regions in the feature maps. To apply these attention weights to the feature maps, a Reshape layer is used to reshape the attention weights into the same spatial dimensions as the feature maps. This ensures that the attention weights can be applied element-wise to each corresponding location in the feature maps.

Subsequently, the reshaped attention weights are multiplied element-wise with the feature maps using the Multiply layer. This step enhances the representation of important features while suppressing irrelevant information. The resulting refined representation is then flattened and passed through dense layers to capture complex relationships between features. Finally, the prediction layer, implemented as a Dense layer with softmax activation, classifies the skin cancer images into the seven types

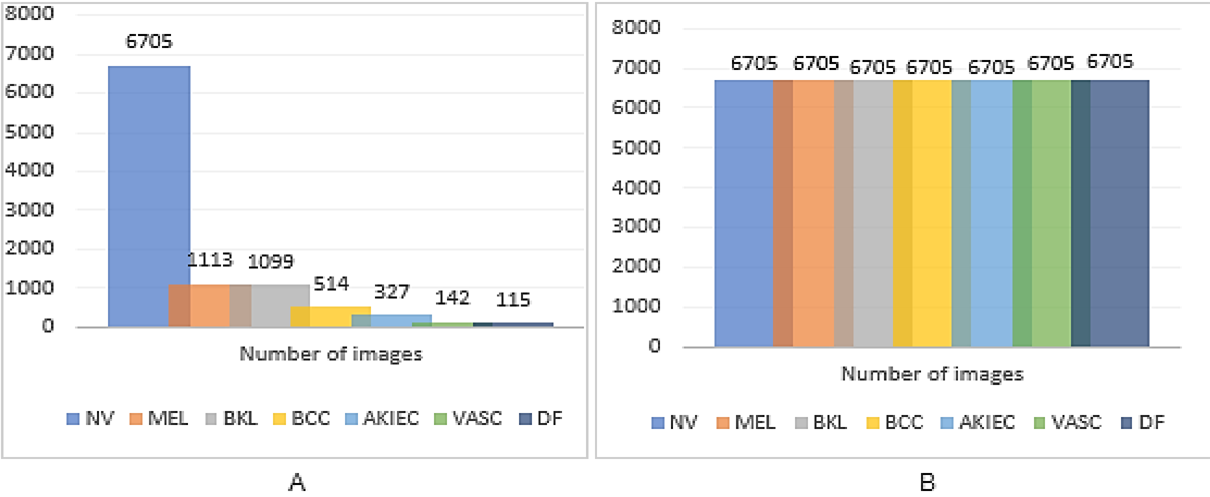

Figure 2. (A) Class distribution of the HAM10000 dataset, (B) the HAM10000 dataset after the SMOTE technique.

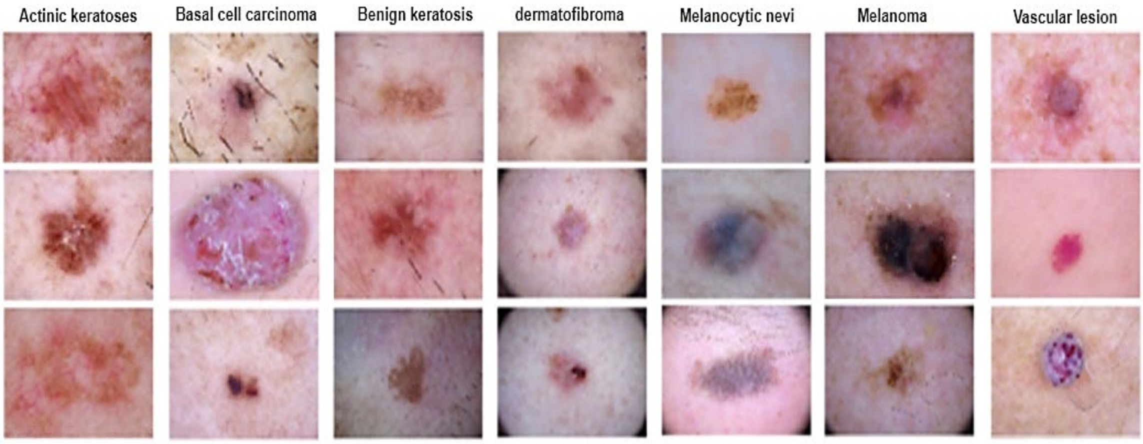

Figure 3. Examples of skin cancer images from HAM10000 dataset (Tschandl, Rosendahl et al. 2018).

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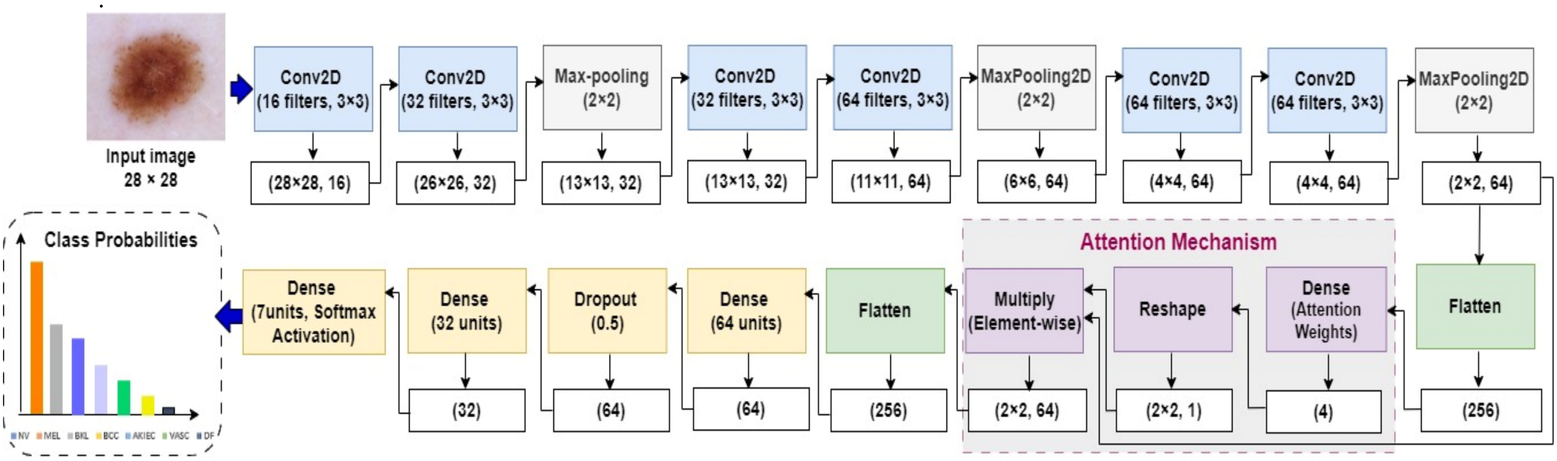

Figure 4. The architecture of the suggested CNN model with attention mechanism for feature extraction.

After the feature extraction process, the extracted features are utilized to create a case base, which plays a crucial role in the Case-Based Reasoning (CBR) system. The case base serves as a repository of previously diagnosed skin cancer cases, including their corresponding features and classifications.

3.3. Suggested retrieval phase based on a modified cascade forest model

To differentiate the seven types of skin lesions in the HAM-SM dataset, we integrated the modified cascade forest model into the retrieval phase of the Case-Based Reasoning (CBR) system. We evaluated its performance against the standard cascade forest model (Zhou and Feng 2017) and traditional Machine Learning (ML) models such as Support Vector Machines (SVM) (Cortes and Vapnik 1995), K-Nearest Neighbors (KNN) (Jiang, Cai et al. 2007), eXtreme Gradient Boosting (XGBoost), and random forest (RF) (Breiman 2001). As a result, the classification or solution for a new case, represented by a set of features in the test case base, corresponds to the class with the highest accuracy achieved by one of these integrated classifiers.

Figure 5 presents the architecture of the modified cascade forest model employed in the retrieval phase. In contrast to solely utilizing the random forest model, we incorporated the XGBoost model in the first layer. The incorporation of XGBoost was motivated by its superior gradient boosting capabilities, which enable more effective ensemble learning and improved predictive performance. Subsequently, in the following layers, we continued to employ the random forest model to leverage its strengths in handling high-dimensional feature spaces and maintaining diversity within the ensemble. Algorithm 2, outlined below, summarizes the steps of our proposed retrieval phase for skin cancer classification.

Algorithm 2: Suggested Retrieval phase algorithm

Input:
- Set of Attributes of the New Case;
- Models: Modified Cascade Forest, Standard Cascade Forest, SVM, KNN, XGBoost, RF;
- Training Case Base of skin cancer;
- Testing Case Base of skin cancer;

Output:
- New Case Solution ← Prediction of the Type of Skin Cancer;

Begin
1. Load Training Case Base;
2. Load Testing Case Base;
3. Train the Models using the Training Case Base;
4. Evaluate the Models using the Testing Case Base;
5. Calculate Performance Measures (Accuracy, Precision, Sensitivity, F-Measure);
6. Select the Model with Maximum Accuracy among the Models;
7. New Case Solution ← Prediction of the Type of Skin Cancer (from the selected Model with Maximum Accuracy);

End

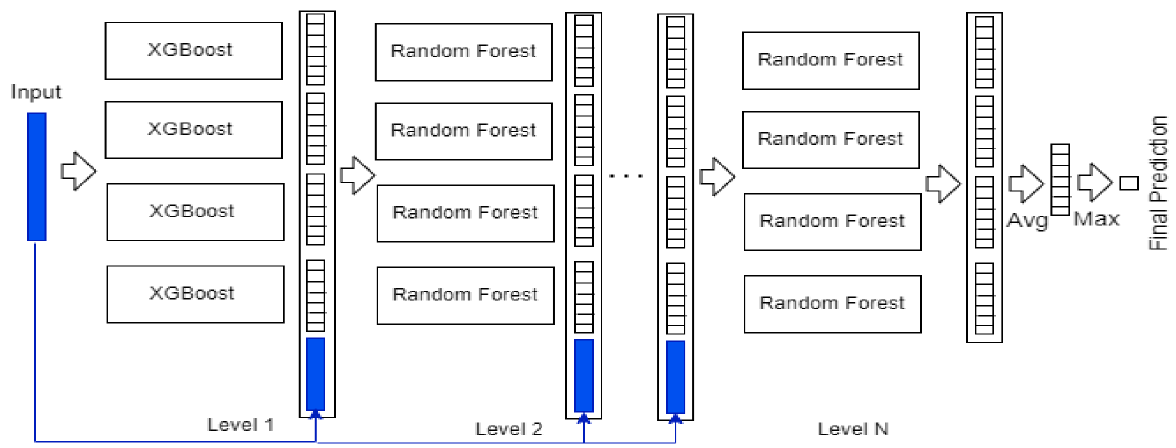

Figure 5. The proposed modified Cascade Forest Model architecture. In each layer, there are four fundamental classifiers that produce probability vectors, serving as augmented features for the subsequent layer's learning process.

Using a CNN with an attention mechanism as a feature extractor alongside the modified cascade forest model offers several advantages over the multi-grained scanning operation. Firstly, the attention mechanism allows the CNN to concentrate on specific regions or features in an input image that are most relevant for the classification task, enhancing the model's ability to capture crucial information. Secondly, unlike multi-grained scanning, which can introduce computational complexity by scanning the input at multiple scales, integrating an attention mechanism within the CNN reduces this burden by selectively focusing computational resources on the informative parts of the image, thus improving overall efficiency. Lastly, skin cancer images exhibit variations in lesion size, location, and appearance. The adaptive nature of the attention mechanism enables the CNN to dynamically attend to different regions of the image, enhancing its robustness and ability to handle diverse lesion characteristics. Consequently, it improves the model's generalization performance.

4. Performance measures

To evaluate the performance of the models used in our retrieval phase for classifying the seven types of skin lesions, we employed standard classification measures including precision, recall, accuracy, and F1-score. The following table 3 summarizes these performance measures:

Table 3. Classification Performance Measures.

Measure	Formula
Precision	TP / (TP + FP)
Recall	TP / (TP + FN)
Accuracy	(TP + TN) / (TP + TN + FP + FN)
F1-score	2 * ((Precision * Recall) / (Precision + Recall))

In the formulas, TP (True Positive) represents the number of positive cases classified correctly, TN (True Negative) represents the number of negative cases classified correctly, FP (False Positive) is the number of positive cases classified as inaccurate, and FN (False Negative) is the number of negative cases classified incorrectly.

5. Results and discussion

This section presents the classification performance of the proposed CNN with attention mechanism, the results of the retrieval phase of the CBR system for skin cancer classification, as well as a comprehensive comparison with other classifiers.

5.1. Performance of CNN model with attention mechanism

To assess the effectiveness of the proposed CNN model with attention mechanism, the network was trained on the HAM-SM dataset using the specified parameters outlined in Table 4. Following the training phase, features were extracted from the images using the trained CNN model. The CNN model with attention mechanism extracted 256 features for each input image. The extracted features from the 37,548 training images were used to build the training case base, while the extracted features from the 9,387 test images were used to build the test case base. These case bases were then employed during the retrieval phase for the skin cancer classification task.

Table 4. The details of the parameters of the CNN model used.

Parameter	Value
Number of Epochs	30
Batch size	64
Learning rate	0.00001
Optimizer	Adam
Activation function	ReLU
Dropout Rate	0.5
Filter Size	3 × 3
Pooling Size	2 × 2

During the training process, the CNN model's accuracy and loss rates were monitored over 30 epochs, as depicted in Figure 6. The training and validation accuracy curves demonstrate the model's learning progress, while the loss curve indicates the convergence of the model. Additionally, the performance of the CNN model with attention mechanism was evaluated, and the detailed results are presented in Table 5.

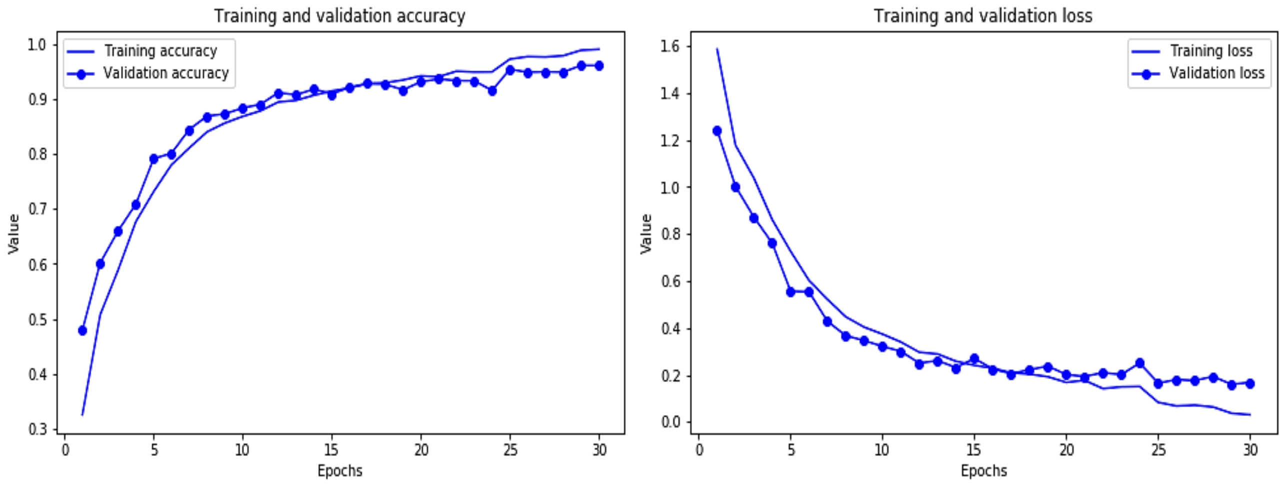

Figure 6. Training and Validation Accuracy and Loss Curves for the CNN Model with Attention Mechanism.

Table 5. Results of the Performance Evaluation of the CNN Model with Attention Mechanism for Skin Cancer Classification

Model	Accuracy %	Precision %	F1-Score %	Recall %
CNN Model with Attention Mechanism	**94.86**	94.87	94.86	94.91

The successful classification results achieved by the CNN model with attention mechanism emphasize its potential as a valuable tool for precise feature extraction from skin cancer images. With an accuracy rate of 94.86%, the CNN model exhibits the ability to accurately classify skin cancer cases. Additionally, the precision, F1-score, and recall values of 94.87%, 94.86%, and 94.91%, respectively, demonstrate the model's effectiveness in reducing both false positives and false negatives.

5.2. Results of the retrieval phase of the CBR system

In this subsection, the results of the retrieval phase of the Case-Based Reasoning (CBR) system for skin cancer classification are presented, comparing the performance of the Standard Cascade Forest Model and the Modified Cascade Forest Model. The evaluation involves varying numbers of layers (NL) and different numbers of trees per classifier (NTC) for random forest or XGBoost, as indicated in Table 6 and Table 7, respectively.

Table 6. Performance Evaluation of the Standard Cascade Forest Model for Skin Cancer Classification.

Model	Standard Cascade Forest Model					
	NL=10, NTC=50	NL=10, NTC=100	NL=50, NTC=50	NL=50, NTC=100	NL=100, NTC=50	NL=100, NTC=100
Accuracy %	91.22	91.11	91.24	**93.04**	90.31	90.13
Precision %	91.79	91.72	91.73	**93.45**	90.41	90.26
F1-Score %	91.21	91.10	91.22	**92.92**	90.28	90.10
Recall %	91.27	91.17	91.29	**93.09**	90.38	90.20

Table 7. Performance Evaluation of the Modified Cascade Forest Model for Skin Cancer Classification.

Model	Modified Cascade Forest Model					
	NL=10, NTC=50	NL=10, NTC=100	NL=50, NTC=50	NL=50, NTC=100	NL=100, NTC=50	NL=100, NTC=100
Accuracy %	94.80	94.99	94.80	94.63	94.35	**95.40**
Precision %	94.87	95.07	94.87	94.73	94.51	**95.49**
F1-Score %	94.77	94.96	94.77	94.60	94.34	**95.38**
Recall %	94.84	95.03	94.84	94.67	94.39	**95.44**

The Standard Cascade Forest Model demonstrates reasonable performance across various configurations, achieving accuracy values ranging from 90.13% to 93.04%, along with consistent precision, F1-Score, and recall scores. In contrast, the Modified Cascade Forest Model consistently outperforms the Standard Cascade Forest Model, achieving higher accuracy values ranging from 94.35% to 95.40%, as presented in Table 8. The precision, F1-Score, and recall values for the Modified Cascade Forest Model also exhibit notable improvements over the Standard Cascade Forest Model. Additionally, Fig.7 provides a visual representation of the predictions made by both models for NL=100, NTC=100. It shows the fraction of predictions that are correct and incorrect, highlighting the superior performance of the Modified Cascade Forest Model.

The improved performance of the Modified Cascade Forest Model can be attributed to its hybrid architecture, comprising an initial layer with an XGBoost model, followed by subsequent layers with random forest models. The inclusion of the XGBoost model in the initial layer allows the Modified Cascade Forest Model to leverage its gradient boosting capabilities, effectively addressing issues like overfitting and gradient vanishing. As a result, the modified model can capture complex patterns and relationships in the data, leading to enhanced accuracy and robustness in skin cancer classification. Moreover, the subsequent layers of the Modified Cascade Forest Model, utilizing random forest models, complement the strengths of the XGBoost model by applying ensemble learning techniques, further enhancing classification accuracy. This combination of diverse machine learning approaches enables the Modified Cascade Forest Model to effectively address the challenges associated with skin cancer classification, such as class imbalance and distinguishing subtle differences between similar skin lesions.

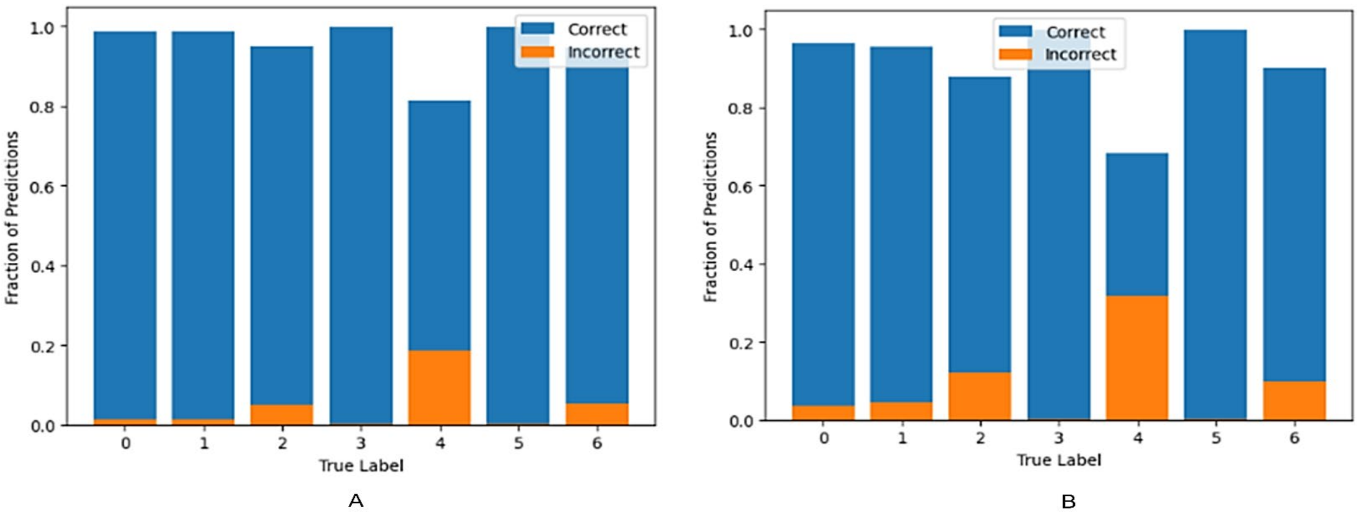

Figure 7. (A) Predictions of Modified Cascade Forest Model for NL=100, NTC=100, (B) Predictions of Standard Cascade Forest Model for NL=100, NTC=100.

To comprehensively assess the effectiveness of the proposed approach, a comprehensive evaluation incorporates the results of other classifiers, including SVM, KNN, XGBoost, and RF models, as displayed in Table 8.

Furthermore, Table 9 presents the performance of these classifiers using the case bases created by the CNN model with attention mechanism from the imbalanced HAM10000 dataset, i.e., without using the SMOTE technique.

The Figure 8 details the confusion matrices of the different models used in the retrieval phase. Additionally, figures 9 and 10, as well as 11 and 12, visually demonstrate a comparison between the classifier's performances with and without the utilization of the SMOTE technique.

Table 8. Performance Evaluation of Models in the Retrieval Phase for Skin Cancer Classification using case base from balanced HAM10000 dataset using SMOTE technique

Model	Accuracy%	Precision %	F1-Score %	Recall %
SVM	94.41	94.45	94.40	94.45
KNN	94.59	94.82	94.52	94.63
XGBoost	95.03	95.09	95.01	95.07
RF	91.45	91.89	91.44	91.53
Standard Cascade Forest	93.04	93.45	92.92	93.09
Proposed Modified Cascade Forest	**95.40**	**95.49**	**95.38**	**95.44**

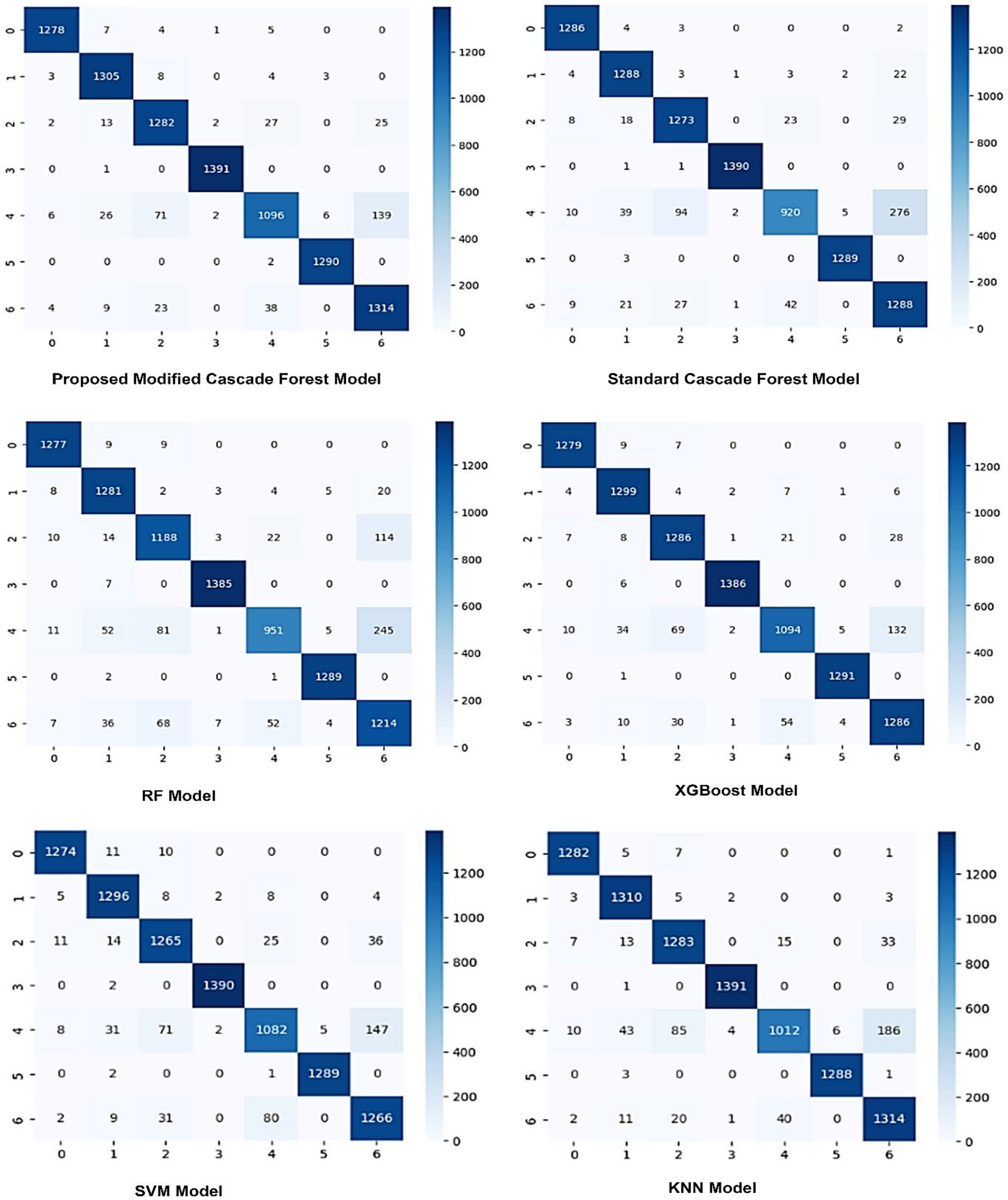

Figure 8. Detailed Confusion Matrices of the Different Models Used in the Retrieval Phase.

Based on the confusion matrices, class 4 appears to pose the greatest challenges for all evaluated models. This suggests that a considerable number of instances from other classes are frequently misclassified into class 4. This confusion could be attributed to significant overlaps in characteristics with other types of lesions. The proposed model misclassified 431 instances, yet remains the top performer overall.

Table 9. Performance Evaluation of Models in the Retrieval Phase for Skin Cancer Classification using case base from imbalanced HAM10000 dataset.

Model	Accuracy%	Precision %	F1-Score %	Recall %
SVM Model	75.63	51.21	47.82	46.07
KNN Model	72.79	47.45	44.87	44.14
XGBoost Model	75.23	62.11	47.99	46.29
RF Model	75.78	50.88	45.13	42.39
Standard Cascade Forest Model	75.73	53.50	47.27	43.75
Proposed Modified Cascade Forest Model	**76.28**	**57.69**	**48.76**	**46.53**

As shown in Tables 8 and 9, our method outperforms the other evaluated models for skin cancer classification, including the powerful XGBoost model, both on the balanced HAM-SM dataset treated with SMOTE (Table 8) and on the imbalanced HAM10000 dataset (Table 9). In the case of the balanced HAM-SM dataset, our proposed approach achieves remarkable performance with an accuracy of 95.40%, a precision of 95.49%, an F1-score of 95.38%, and a recall of 95.44%. Although the individual XGBoost model also obtains excellent results, our method slightly outperforms it on all the evaluated metrics.
This marginal superiority suggests that our cascade architecture captures subtle patterns and relationships that are not entirely captured by a single model, even as powerful as XGBoost. The integration of XGBoost in the first layer, followed by random forests in the upper layers, seems to enable a more fine-grained modeling of the complex interactions present in the data.
However, it is on the imbalanced dataset that the advantages of our approach become even more evident. In this more challenging context, our proposed method maintains significantly superior performance compared to XGBoost and the other evaluated models, with an accuracy of 76.28%, a precision of 57.69%, an F1-score of 48.76%, and a recall of 46.53%.
These results highlight the robustness of our approach in the face of the challenges posed by imbalanced datasets, where the ability to capture complex patterns and handle minority classes is crucial.
Additionally, as shown in Table 1, the suggested Modified Cascade Forest Model consistently outperforms the majority of the listed models in terms of precision classification for skin cancer.

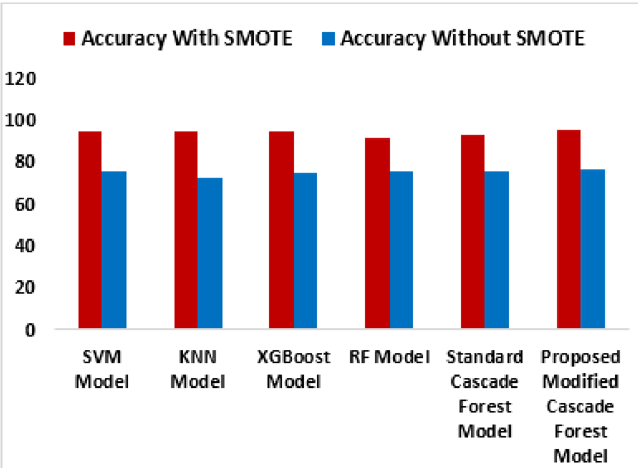

Figure 9. Accuracy of different classifiers with and without the use of the SMOTE technique on the HAM10000 dataset.

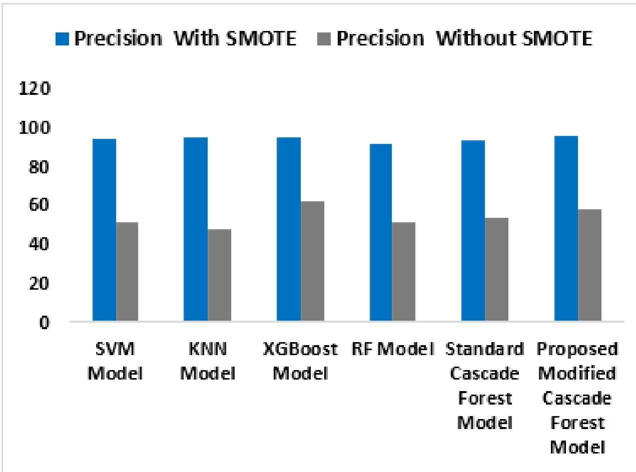

Figure 10. Precision of different classifiers with and without the use of the SMOTE technique on the HAM10000 dataset.

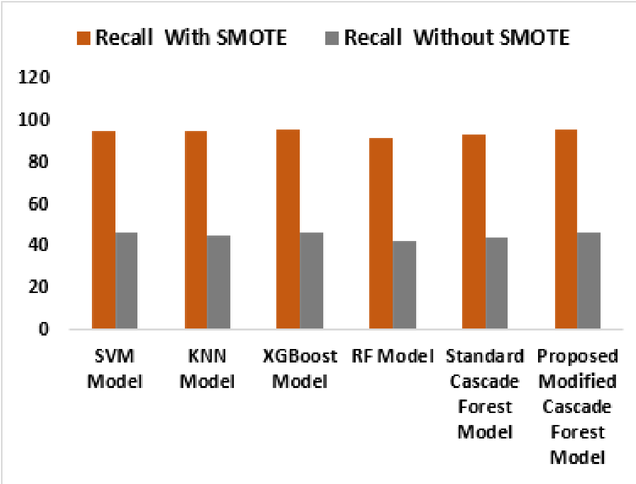

Figure 11. Recall of different classifiers with and without the use of the SMOTE technique on the HAM10000 dataset.

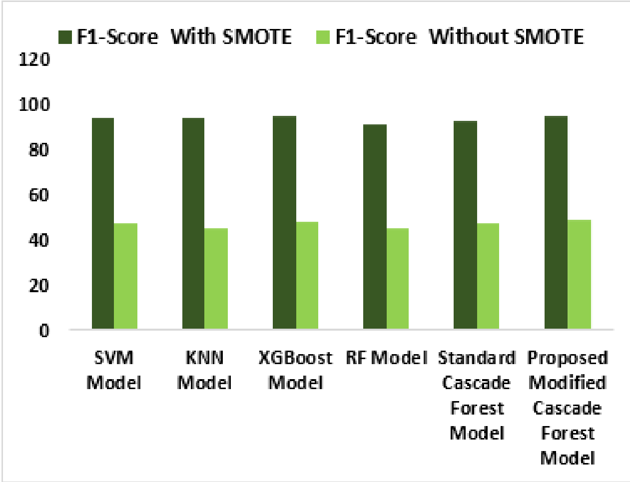

Figure 12. F1-Score of different classifiers with and without the use of the SMOTE technique on the HAM10000 dataset.

6. Conclusion and future work

The timely and precise diagnosis of skin cancer holds immense significance in the realm of healthcare, serving as a linchpin for guiding tailored treatments and impeding the advancement of this insidious disease. Detecting skin cancer in its incipient stages is pivotal, as it allows for more effective therapeutic interventions, ultimately leading to improved patient outcomes. Skin cancer, with its multifarious subtypes and intricate manifestations, poses a diagnostic challenge to healthcare professionals, making it imperative to explore innovative methodologies that augment the accuracy and efficiency of its classification.

This study proposes an innovative approach to enhance the retrieval phase of the CBR system in the medical domain, aiming to effectively identify optimal solutions for new skin lesion cases. The approach leverages the power of the convolutional neural network with an attention mechanism to extract relevant features from skin lesion images and utilizes the modified cascade forest model for classification.

Through experimentation on the HAM10000 dataset, the approach achieved a remarkable classification accuracy of 95.40%, showcasing its reliability and outperforming several other skin lesion classification methods.

In the future, the focus will be on refining the feature extraction and classification process by incorporating various robust deep learning models and exploring additional skin cancer datasets. By continuously enhancing the model's capabilities, the aim is to further improve the accuracy and efficiency of skin cancer classification, ultimately contributing to more effective healthcare practices.

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