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Article

Enhancing Skin Lesion Classification Using Few-Shot Learning: Addressing Data Scarcity in Rare Lesion Diagnosis

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Abstract: Accurate skin lesion detection and identification of types of lesions is crucial. It can also be difficult because of the scarcity of clinical data, especially for uncommon types of skin lesions. Classification between various skin conditions that may look similar visually is also a challenging task. In order to address these issues, we have proposed a skin lesion classification methodology built on a Siamese network with a fusion of attention mechanisms and few-shot learning to focus on identifying important and distinctive features from the images. Our classification framework is designed to perform well even with limited training data, allowing it to classify skin lesions into multiple classes even in challenging and complex scenarios. This methodology of multi-class classification is based on a novel approach to learning efficiently from sparse data by combining few-shot learning, attention mechanisms, and prototype-based ensemble classification. For classification, the proposed algorithm was trained on the HAM10000 image dataset, and the testing was performed on the ISIC 2018 skin lesion dataset. In this approach, we performed multi-class classification using Support Vector Machine (SVM), Random Forest (RF), K-Nearest Neighbor (KNN), and XGBoost classifiers, as well as a Voting classifier. Our classification method integrates these individual classifiers into one ensemble model. The integration of a Siamese network with a Voting Classifier produced strong classification performance across all evaluation metrics. Experimental evaluation demonstrated consistent performance, achieving an accuracy of 97.42%, a precision of 97.31%, a recall of 97.55%, and an F1-score of 97.38%.These findings demonstrate the effectiveness of the hybrid approach in reliably distinguishing different categories of skin lesions.The framework is particularly suitable for applications where the availability of labeled medical data is limited, providing a robust solution that can assist clinicians in improving diagnostic consistency and supporting early identification of skin lesions...
Keywords: Dermoscopic image analysis, Few-shot learning, Metric learning, Hybrid classification framework, Computer-aided diagnosis

1. Introduction

Skin cancer is a major contributor to the global burden of disease, with melanoma responsible for the highest number of fatalities among skin cancer types. Reports from the World Health Organization (WHO) show that both melanoma and non-melanoma skin cancers affect millions of individuals each year. Timely detection plays a critical role in successful treatment; however, visual similarities between benign and malignant lesions often make clinical assessment difficult, leading to potential diagnostic uncertainty. This underscores the substantial health burden posed by skin cancer [1]. Figure 1 illustrates the total global incidence and rates of skin cancer in 2022, along with the statistics for both men and women.

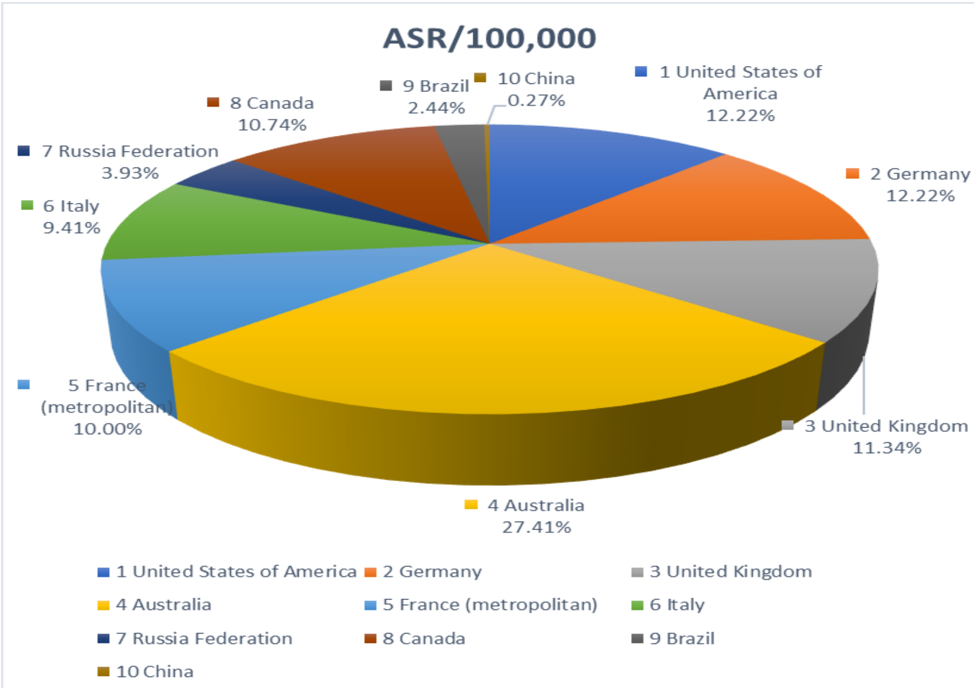

Figure 1. Skin cancer rates globally in 2022 [2]

As illustrated in the figure, Australia exhibited the highest incidence of skin cancer in 2022, with Denmark ranking second [2]. Age-standardized rates (ASRs), which account for differences in population age distribution, provide a standardized basis for comparing disease incidence across countries and reveal substantial geographic variation in the global burden of skin cancer [2].

Early detection of skin cancer is essential for improving treatment outcomes and reducing disease-related mortality. Despite advances in dermatological imaging, distinguishing malignant lesions from benign abnormalities remains difficult, often requiring expert interpretation and histopathological confirmation. Although these methods remain the clinical standard, they can be resource-intensive and may introduce variability in diagnosis due to differences in clinical expertise. These limitations motivate the development of automated methods that can support clinical decision-making and improve diagnostic consistency [3,4]. The increasing application of intelligent computational techniques in healthcare has enabled the development of decision-support systems that improve diagnostic efficiency, reduce manual workload, and facilitate more consistent clinical evaluations [5].

Convolutional neural networks (CNNs) have demonstrated strong performance in medical image analysis across diverse applications [6]. However, these models typically require large annotated datasets for effective training. Conventional supervised approaches suffer when there is not enough high-quality labeled data in the available training set, resulting poor generalization with high misclassification rates, especially for rare skin lesion types. The limitations imposed by the requirement of large data sets were addressed by the emergence of few shot learning, a paradigm that is intended from the outset to operate in very low data environments. Few-shot learning makes use of prior knowledge to generalize from a less number of labeled dataset. Few-shot learning with the Siamese networks is one of the best methods when the data is limited. In the Siamese (dual branch) network, the train and the test images are compared which are processed in two separate branches to determine how similar these two images are. The Siamese network, by comparing a limited number of examples from the test dataset, enables them to find new classes. For the classification of different skin lesions from the limited dataset of rare skin diseases, such a method has proven to be helpful where the most important and contributing features are extracted. The network focuses on important details like uneven edges, uneven colors, or unique texture patterns that could be signs of cancer rather than processing the entire image equally. By focusing on these important characteristics of extracted features, concatenation of selected features is performed followed by attention mechanism. The use of attention mechanisms further improves the model by helping it focus on the most contributing features extracted from an image. This study aims to develop a robust framework for multiclass skin lesion classification, with particular emphasis on improving the recognition of rare lesion categories. The objectives of the study are as follows:

Implement a Siamese network to extract discriminative features, enabling effective learning from limited labeled examples.

Integrate attention mechanisms to emphasize critical image features, improving recognition of subtle inter-class differences.

Develop a system using extracted features to create class prototypes, facilitating accurate classification through distance metrics for multi-class lesion categorization.

This research aims to advance dermatological diagnostics by improving automated skin lesion classification systems' accuracy and reliability, particularly in environments where data is scarce. This approach could help bridge the gap between the need for accurate diagnoses and the challenges of not having enough training data for rare lesion types.

2. Related Works

Recent developments in machine learning and image processing has enabled more accurate and efficient analysis of medical images. Also, the accuracy and speed of these processes have improved tremendously. Related works section introduces state-of-the-art techniques with their various approaches which have resulted in a significant boost in the skin lesion analysis.

Khan et al. [8] used probabilistic distribution and entropy-based theories for feature selection and segmentation to achieve high accuracies using ISBI and PH2 datasets. Jayapariya et al. [9] fused the features extracted by VGG16 and GoogleNet as well as their model, handcrafted features, which improved segmentation performance. Similarly, Adjed et al. [11] used Curvelet and Wavelet transforms to extract structural features, obtaining promising results.

In a study [10], Tschandl et al. focused on the classification task and trained their deep convolutional neural networks (CNNs) on ISIC 2017 dataset by using ResNet34 layers to segment the skin lesions effectively. It was possible to transfer the performance of the pre-trained layers for the task of lesion segmentation. Mahbod et al. [12] researched how the preponderance of resizing an image affects skin lesions classification with the use of a pre-trained CNN model. They performed image resizing on six different scales and test classification performance against three CNN models which are SeReNeXt-50, EfficientNetB0 and EfficientNetB1 respectively. In addition, they proposed a fusion of multi-scale multi-CNN (MSM-CNN) models based on an ensemble learning approach where these models were trained on images of different sizes after being cropped. Their approach using MSM-CNN on ISIC 2018 dataset achieved 86.2% accuracy and noted that cropping the images resulted in better outcomes than scaling.

After extensive testing with a variety of pre-trained convolutional neural network (CNN) models, Chaturvedi et al. [13] developed a system for multiclass skin cancer classification. They achieved 93.2% accuracy in multiclass classification using transfer learning with models such as Inception and ResNetXt-101. In another study, Kawahara et al. [14] explained how a linear classifier was built using a dataset of 1300 images and skin cancer features extracted from a deep convolutional neural network. In their experimentation, they performed classification into five and ten classes, and reached accuracies of 85.8% and 81.9%, respectively.

Alquran et al. [15] introduced a method that uses an SVM classifier, achieving an impressive accuracy of 92.1% in identifying, extracting, and classifying tumors from dermoscopy images. This approach has significantly helped in classifying both benign and melanoma skin cancers. In another study, on the ISIC 2018 dataset, Majtner et al. [16] discussed an ensemble learning method based on GoogleNet and VGG-16 model. The method along with data augmentation and color normalization techniques resulted in an accuracy of 80.1%. Additionally, Lopez et al. [17] used VGGNet and transfer learning technique to classify benign and malignant skin cancers on the ISIC dataset, reaching an accuracy of 81.3%.

Some of the deep learning applications such as machine translation, image and video captioning, and image understanding and analysis as well as Visual Question Answering (VQA), have seen the most growth where the attention mechanism was used [18]. For example, VGGNet is used along with an attention module to generate attention maps that highlight the critical areas to classify skin lesions efficiently [19]. Although attention mechanism techniques can enhance model performance, they also have limitations, particularly concerning the significant processing overhead caused by the extra parameters needed to learn the attention weights [20]. While recent advances in meta-learning have made it much easier to adapt to new environments where data is limited. Situations in which there aren't many labeled datasets from the target domain available is the supervised domain adaptation [21], one successful strategy for few-shot learning (FSL). An enhanced version of Relation Networks, for example, has been shown by Liu et al. [22] for effective skin condition classification. Battle et al. [23] reported that their approach achieved impressive top-1 classification accuracies of 85.61% on skin disease datasets and 74.33% on clinical datasets.

Lin et al. [24] developed a framework that integrates four different learning models was for binary classification. They have initially performed image segmentation using a discriminator followed by a binary classifier that separates the skin in the foreground from the background. They have also performed multi-class classification with the help of an autoencoder that creates keyword labels by extracting features from the autoencoder and the discriminator. Additionally, a Siamese network was used to evaluate the similarity between skin condition descriptions and common keywords. The results of this approach were quite impressive, with an accuracy of up to 99% in translating spoken language related to skin images, which helps users understand dermatological conditions better. This work presents a good prospect for utilizing Siamese networks in the future, particularly in a clinical setting, while identifying some areas that can be reformed and affected in medical contexts.

Limited annotated data remains a major challenge in skin lesion classification. To address this issue, a Siamese network integrated with an attention module is proposed to improve feature learning and classification performance using few training samples.

3. Materials and Methods

Datasets

The proposed study uses the ISIC 2018 dermoscopic image dataset provided by the International Skin Imaging Collaboration (ISIC) [25]. The classification dataset consists of 11,527 images, including 10,015 training and 1,512 testing samples. In contrast to the ISIC 2016 and 2017 datasets, which contained two and three lesion classes, respectively, ISIC 2018 includes seven lesion categories for multiclass skin lesion classification. Ground-truth data for training included seven classes: melanoma (MEL), basal cell carcinoma (BCC), vascular lesions (VASC), actinic keratosis/Bowen’s disease (AKIEC), dermatofibroma (DF), melanocytic nevus (NV), and benign keratosis (BKL) [26], as shown in Figure 2.

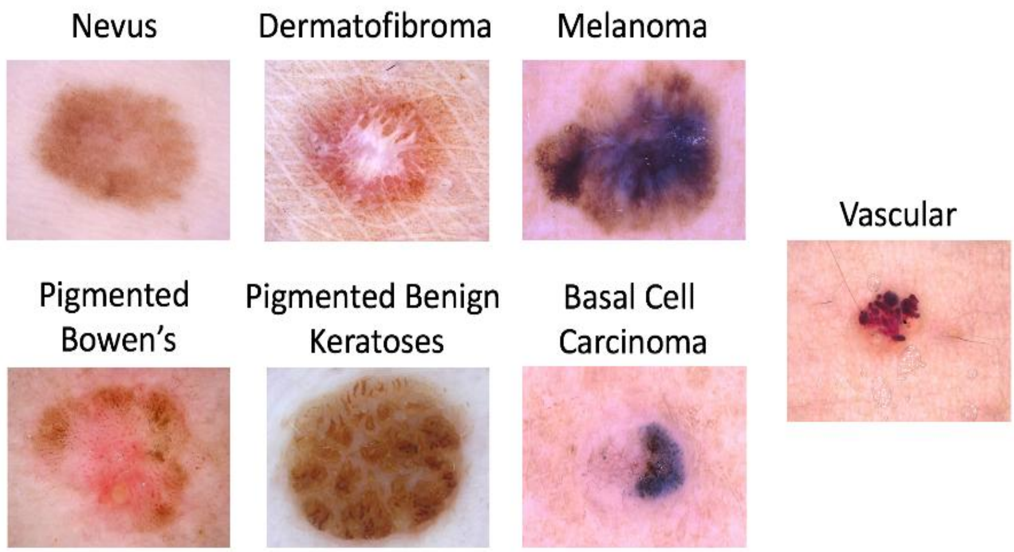

Figure 2. ISIC 2018 skin lesion dataset with different types of skin lesions

Proposed Methodology

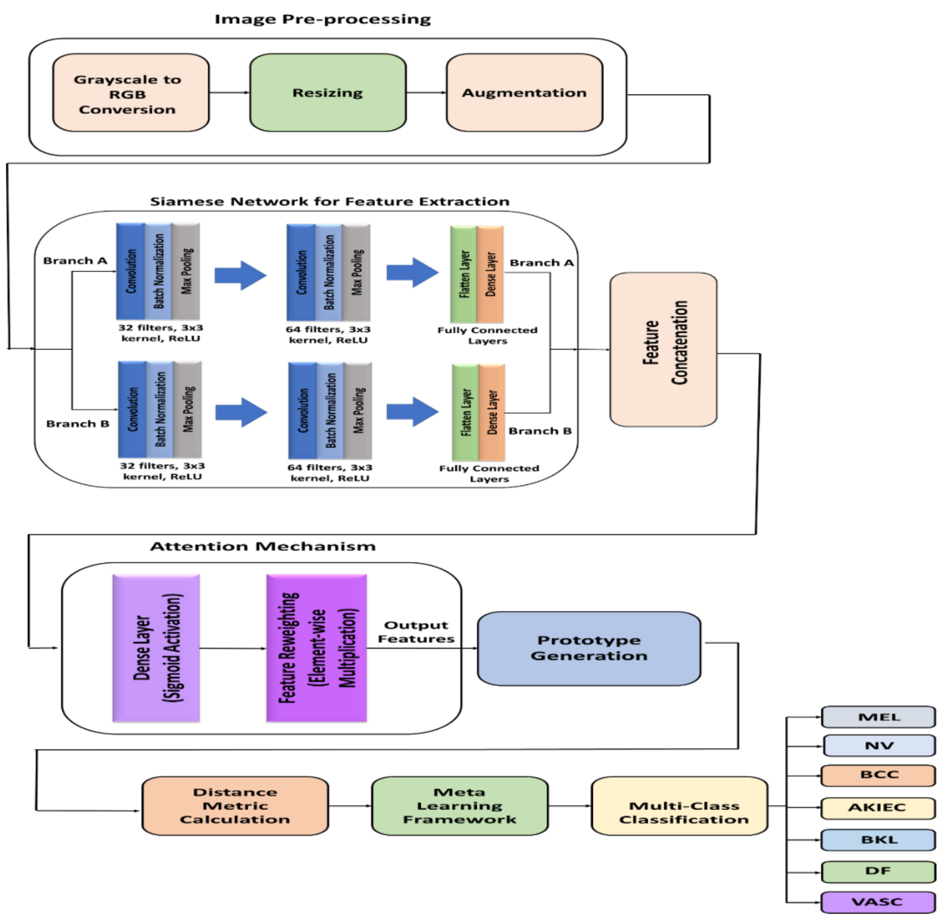

Figure 3. Proposed methodology for multi-class skin lesion classification

This section presents the developed system for skin lesion classification into the multiple classes, Figure 3 depicts the utilization of several key components: a dual-branch feature extractor, an attention mechanism, prototype generation, distance metric learning, and a meta-learning framework.

Image Pre-processing

Pre-processing of images is an important component in the process of generation of the dataset for skin lesion classification [27]. The image upscaling tasks performed in this sequence include: converting grayscale images to RGB, scaling and normalization of the images and performing data augmentation to increase the robustness of the model. All the images in grayscale color are transformed to RGB images for CNNs. All images are converted to the RGB color space and resized to 224 × 224 pixels to satisfy the CNN input requirements. Bilinear interpolation is used to generate images of 224 × 224 pixels with minimal distortion. Data augmentation is performed on the training dataset to improve model robustness and minimize overfitting [28]. Figure 4 presents sample images generated using the applied augmentation techniques.

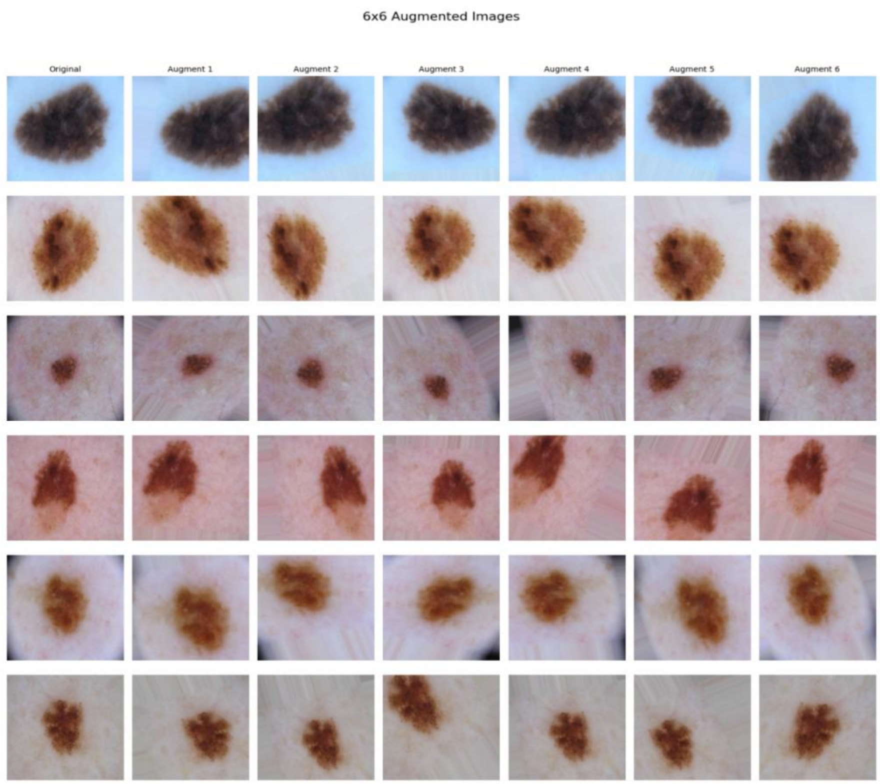

Figure 4. Augmented data samples using rotation, flip, sheer, zoom, etc.

Siamese Network for Feature Extraction

For effective feature extraction, Siamese Network architecture is used, which is particularly beneficial for tasks with limited labeled data. Siamese networks consist of two identical subnetworks that process two input images and compare their feature representations. The output is typically a similarity score, indicating whether the images belong to the same class. This architecture is made up of two identical subnetworks that utilize the same parameters and weights, ensuring that both branches extract similar features from different input images. As indicated in Figure 3, Branch A processes the support set that consists of a few labeled images while Branch B processes the query image which needs to be classified. Each branch contains several convolutional layers, which extract the important features from the images followed by batch normalization layers, which stabilize the learning process. After each convolutional layer, ReLU activation functions have been applied to introduce non-linearity, such that the network can capture all the complex patterns in data. This architecture enables effective feature extraction from both the support set and the query image, such that it forms a basis for subsequent distance metric learning and classification tasks. In Figure 5, the number of features extracted from Image A input to branch A and image B as the query image. Through feature extraction, the Siamese Network compares the two images and concludes how similar the two images are, thus being able to accurately determine the class of the query image based on the characteristics of the supporting image. Subsequently, the features from Branch A and Branch B are taken and their respective features are joined together. The model thus forms an informative vector that combines the captured features of both the training set and the test set images.

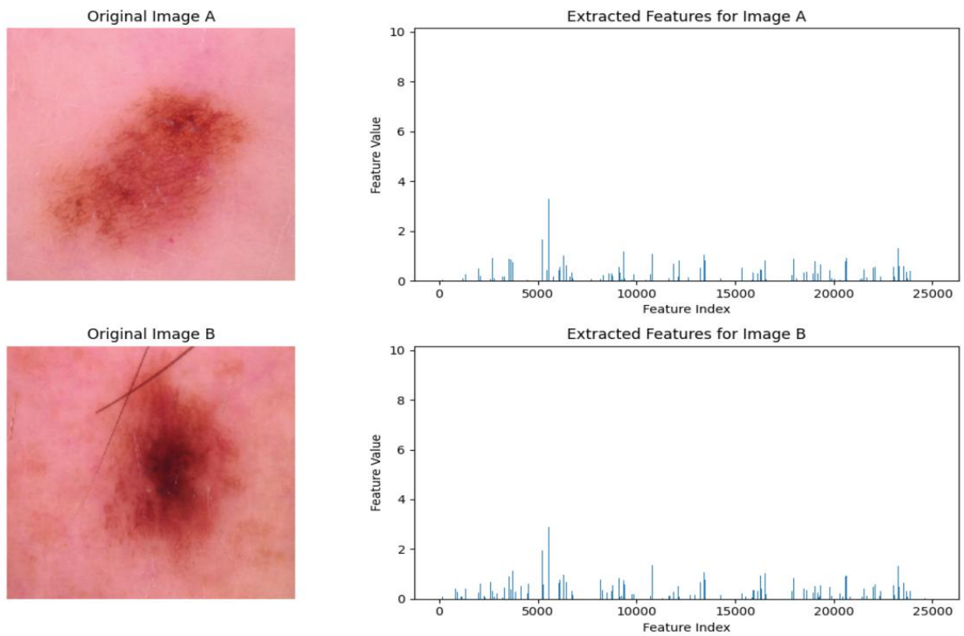

Figure 5. Features extraction from sample images using Siamese Network

Attention Mechanism

The attention mechanism is a method that allows the model to concentrate on particular areas of the input data, enhancing the encoding of important features while ignoring those that are less informative. In our proposed method of skin lesion multi-class classification, the fact that a mechanism of attention is employed after feature concatenation has advantages in the sense that it supports required features that are crucial in differentiating between skin lesions. The attention scores generated by the mechanism also indicate the portion of images that are critical in the decision-making by the other models of the system. The attention mechanism is crucial in directing the model to relevant parts that matter during classification, and as a result, improves classification performance, which is especially beneficial when the datasets are small or have class imbalance problems [29].

The procedure in an attention mechanism block starts by using a fully connected layer that employs a sigmoid activation function in which the layer generates a set of attention scores for the concatenated features, thus focusing on the crucial components which are informative for the classification.

$$A_{attention} = (W_{dense} . F_{concat} + b_{dense}) \quad (1)$$

The element-wise multiplication is performed on the resulting scores which are then utilized for feature reweighting.

$$W_{FConcat} = (A_{attention} \odot F_{concat})$$

(2)

Prototype Generation

At this stage, class prototypes are formed by means of the weighted features that have been derived from the support set. The classification of support vectors is such the prototype belonging to each class acts as the feature vector of that class. Following are the steps to define class prototypes:

Weighted Feature Extraction: After applying the attention mechanism, each class in the support set will have its weighted features denoted as W FA. This ensures that more informative features plays an important role in the prototype representation.

Mean Calculation: For each class *c*, calculate the prototype *Pc* by taking the average of the weighted features.

$$Pc = \frac{1}{Nc} \sum_{i=1}^{Nc} \quad W\,F_{Ai} \tag{3}$$

Where, *Nc* denotes the total number of samples in class *c* and WFAi represents the weighted feature vector for each sample *i* in class *c*.

Storage of Prototypes: These prototypes are stored for later comparison with the features of query image.

Distance Metric Calculation

After generating the class prototypes, the subsequent step is to assess the similarity between the features of the query image and the class prototypes. A distance metric plays an important role in the classification process:

Extraction of Features for Test (Query) Image: Extract the features from the test image after passing it through the dual-branch network, resulting in a feature vector F*B*.

Distance Calculation: Use a suitable distance metric to calculate the similarities between the query feature vector and each class prototype. Commonly used metrics include:

Cosine Similarity: This calculates the cosine of the angle between two vectors, providing a normalized similarity score:

$$Cosine\ Similarity = \frac{F_B . F_C}{||F_B||\ ||F_C||} \tag{4}$$

The class exhibiting the highest similarity score to the test image feature will be assigned as the predicted label.

Meta-Learning Framework

The Meta-learning framework enables the model to learn only from few number of examples efficiently by simulating tasks that reflect the difficulties of few-shot learning [30]. The model is exposed to a variety of tasks during the training process each of which consists of a few samples with labels and an unlabelled query set, to foster the development of generalization abilities across categories [31].

By modifying its parameters for each task to minimize classification errors, the model improves its ability to learn new classes. It can efficiently classify new samples even with sparse data, by using information from the previous tasks. Through this iterative process The model's parameters are refined and in rare instances, it even improves its ability to recognize skin lesions in practical situations. Ultimately, the model performs well in environments with little data with the the meta-learning framework.

Multi-Class Classification

The ISIC 2018 dataset encompasses seven different types of skin lesions: melanocytic nevus (NV), dermatofibroma (DF), actinic keratosis/Bowen's disease (AKIEC), vascular lesions (VASC), melanoma (MEL), basal cell carcinoma (BCC), and benign keratosis (BKL). Accurate Multi-class lesion classification is enhanced by using several classifiers in an ensemble learning approach to boost accuracy and reliability [32]. Initially, we performed multi-class classification with Random Forest (RF), Support Vector Machine (SVM), K-Nearest Neighbor (KNN), and XGBoost classifiers. We then compared their results with a Voting classifier, which integrates these individual classifiers into one ensemble model [33, 34]. We have noticed that with the use of ensemble learning, multi-class lesion classification was enhanced in terms of accuracy and reliability.

The risk of overfitting in skin lesion classification can be reduced by utilizing multiple models, which mitigates the limitations of individual models [35]. As the SVM classifier performs exceptionally well in high-dimensional spaces and manages non-linear relationships, we have used it as the base classifier in the ensemble learning approach for the Voting classifier. The Voting Classifier's overall effectiveness was further improved by incorporating Bagging and Boosting methods. For stability, Bagging trains multiple classifiers on different data subsets, while the errors of prior classifiers can be sequentially corrected by Boosting technique. Algorithm 1 shows, the step-by-step execution of Multi-class classification using the proposed methodology.

Algorithm 1: Bagging and Boosting algorithm for multi-class Classification using Voting classifier

Define the number of base classifiers N for both Bagging and Boosting.

Set the number of classes C in the multi-class classification problem.

Choose hyperparameters for the SVM classifier.

Bagging Process:

Step 1: *Generate N subsets from the training dataset through random sampling with replacement, a method known as bootstrap sampling.*

Step 2: *For each subset:*

Train an SVM classifier SVMi on the subset.

Step 3: *Store the predictions from each trained SVM classifier for the validation/test dataset.*

Boosting Process:

Step 4: *Initialize weights for all training instances (e.g., equal weights).*

Step 5: *For n iterations (e.g., N):*

Train a new SVM classifier SVMn on the training dataset, using the current weights.

Make predictions on the training data.

Calculate the classification error for SVMn

Update the weights of the misclassified instances to focus more on them in the next iteration.

Store the trained classifier SVMn and its weight based on its performance.

Voting Classifier:

Step 6: *Combine the predictions from both Bagging and Boosting:*

For each test instance, collect predictions from all Bagging classifiers SVMi and Boosting classifiers SVMn.

Step 7: *Implement a voting mechanism:*

For each test instance, count the votes from the Bagging classifiers and Boosting classifiers.

Use majority voting for Bagging predictions and weighted voting for Boosting predictions based on classifier weights.

Final Prediction:

Step 8: *Assign the label to the class with the highest vote count as the ultimate prediction for each test instance.*

Evaluation:

Step 9: *Assess the accuracy, precision, recall, and F1-score for the proposed model.*

Execution of Algorithm 1 enhances the Voting Classifier's ability to deliver more precise, and correct classification of different skin lesion classes in clinical environments.

4. Results and Discussion

In this section, we present the outcomes of the experimentation performed on ISIC 2018 dataset for skin lesion classification. We have also performed detailed analyses of various performance evaluation metrics.

Performance Metrics

The performance of the model was assessed across the seven classes in the ISIC 2018 dataset, using common metrics like precision, recall, F1-score, and accuracy.

Accuracy: It refers to accurately classified instances out of total instances.

$$Accuracy = \frac{TP+TN}{TP+TN+FP+FN} \quad (5)$$

Where, TP is True Positives: a positive image is truly identified as positive.

TN (True Negative): a negative image is truly identified as negative.

FP (False Positive): incorrect prediction of an image as positive when it's negative.

False Negative (FN): incorrect prediction of an image as negative when it's positive.

Precision: It is the positive detection to the ground truth. It represents how many of the images segmented are matching to the ground truth.

$$Precision = \frac{TP}{TP+FP} \quad (6)$$

F1-Score: It provides the harmonic mean of precision and recall, by balancing between the two measures, and is defined as:

$$F1 - Score = 2\ X \frac{Presion\ X\ Recall}{Precision+Recall} \quad (7)$$

Sensitivity (Recall): Sensitivity measures the models' capability to correctly detect positive instances:

$$Sensitivity = \frac{TP}{TP+FN}$$

(8)

4.2. Performance Evaluation of Different Classifiers:

The performance of various classifiers—Random Forest (RF), Support Vector Machine (SVM), K-Nearest Neighbors (KNN), XGBoost, and an ensemble voting classifier—was evaluated for classifying skin lesions using the ISIC 2018 dataset. The distribution of test images across the classes is as follows: 43 images for AKIEC, 93 for BCC, 214 for BKL, 44 for DF, 171 for MEL, 909 for NV, and 35 for VASC. Their effectiveness was compared using metrics such as sensitivity, specificity, F1-score, and accuracy.

Among the evaluated models, XGBoost achieved the highest individual performance, with a precision of **89%**, recall of **87%**, F1-score of **88%**, and accuracy of **92%**. SVM followed with an accuracy of **91%**, demonstrating effective discrimination in high-dimensional feature spaces but reduced performance for overlapping classes. Random Forest achieved **90%** accuracy and effectively captured non-linear relationships, although its decision boundaries were less precise for complex feature distributions. KNN showed comparatively lower performance because of its sensitivity to noisy and high-dimensional features. The superior performance of XGBoost can be attributed to its gradient-boosting strategy, which enabled more effective feature learning and class discrimination.

[Image could not be embedded — unsupported format]

Figure 6. Confusion Matrices of Random forest (a), SVM (b), KNN(c), and XGBoost classifier (d)

*[Image could not be embedded — unsupported format]*The Voting Classifier achieved the highest overall performance among the evaluated models. By combining the outputs of multiple classifiers, it improved classification consistency across lesion categories. The corresponding confusion matrix is shown in Figure 7

Figure 7. Confusion Matrix of Voting Classifier

Table 1. Evaluation metrics of classification using various classifiers

Model	**Accuracy (%)**	**Precision (%)**	**Recall (%)**	**F1-Score (%)**
SVM	91.1	88.7	85.6	86.3
Random Forest (RF)	90.7	85.1	80.2	82.5
KNN	89.9	86	84.8	85.4
XGBoost	92.3	89.7	87	88.2
Proposed Methodology using Voting Classifier	**97.42**	**97.31**	**97.55**	**97.38**

Table 1 compares the performance of the evaluated classifiers. The proposed Voting Classifier achieved the best overall performance, with an accuracy of **97.42%**, precision of **97.31%**, recall of **97.38%**, and an F1-score of **97.55%**. **Figure 8** illustrates the predicted class distribution for the seven skin lesion categories

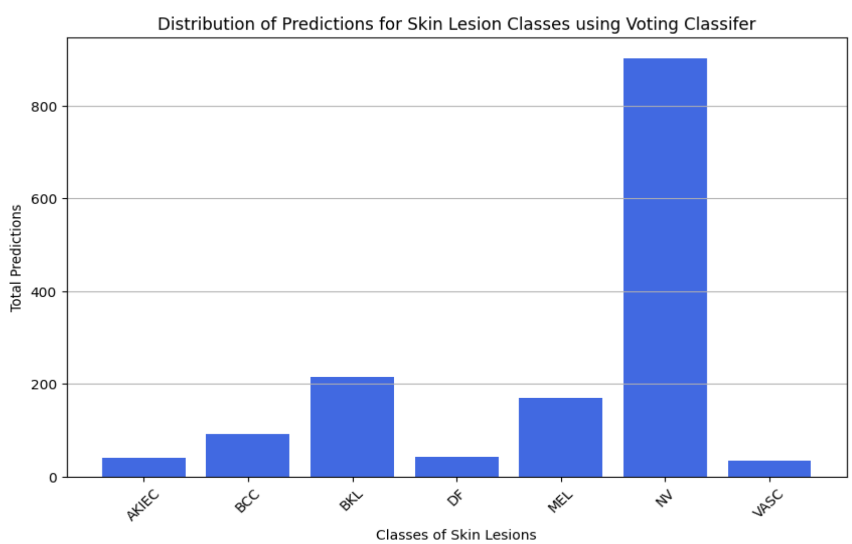

Figure 8. Distribution of prediction of the various classes of skin lesions

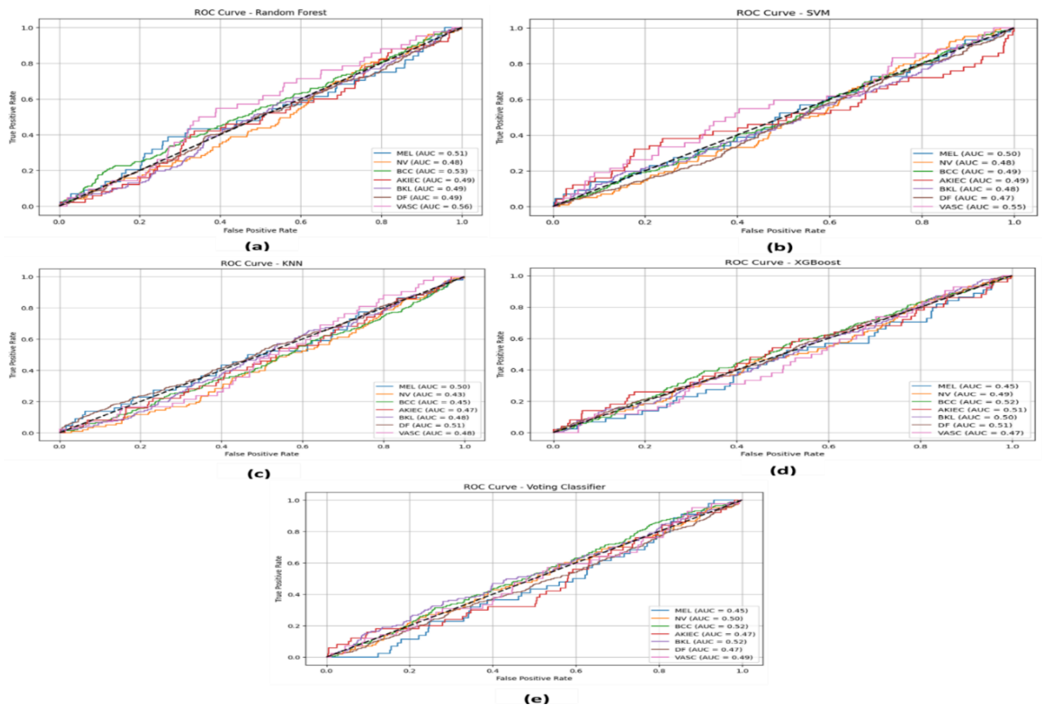

Figure 9 **presents the ROC curves of the RF, SVM, KNN, XGBoost, and Voting Classifier for the seven classes of the ISIC 2018 dataset. Each curve represents the relationship between the true positive rate and false positive rate over a range of decision thresholds.**

Figure 9. ROC Curves of various classifiers; Random forest (a), SVM (b), KNN(c), XGBoost classifier (d), and Voting Classifier (e) for seven classes of skin lesion from the dataset

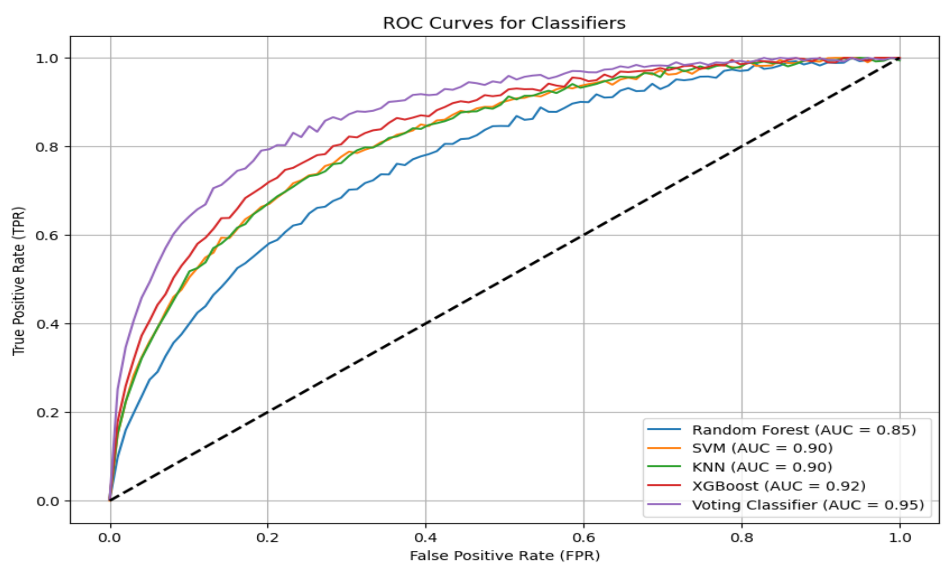

Figure 10 compares the ROC curves of the evaluated classifiers. The AUC values provide an overall measure of classification performance across the seven skin lesion classes. XGBoost achieved the highest AUC (**0.92**), followed by SVM (**0.90**) and KNN (**0.90**), whereas the Voting Classifier and Random Forest each obtained an AUC of **0.85**.

Figure 10. Combined ROC Curves of various classifiers; Random forest, SVM, KNN, XGBoost classifier, and Voting Classifier

Table 2 shows an analysis that compares the different models for skin lesion classification on the ISIC 2018 dataset. The performance of various models vs. the proposed model is represented concerning evaluation metrics like sensitivity, accuracy, and F1-score.

Table 2. Comparative Analysis of Various state-of-art classification models

Classification Models	**Sensitivity (%)**	**Accuracy (%)**	**F1-Score (%)**
Inception-v3 [36]	77.88	88.05	77.84
ResNet-50 [36]	81	89.28	81.28
Inception-ResNet-v2 [36]	78.18	87.74	78.46
DenseNet-201 [36]	79.57	88.7	79.47
Deep CNN [13]	83	83.15	83
Deep CNN [37]	88.75	88.75	89.11
CNNs With Patch-Based Attention [38]	75.7	–	82.6
Multi-scale and multi-network ensemble [39]	–	86.2	–
Unsupervised Deep Clustering [40]	77.69	91.89	77.92
FixMatch-LS [41]	74.18	93.25	64.15
LSNet [42]	85.7	96.9	-
Few-shot learning framework powered by a Siamese network (Proposed Model)	**97.55**	**97.42**	**97.38**

The results in Table 2 indicate that the proposed framework effectively combines complementary feature extraction and classification strategies. This approach achieved an F1-score of 97.38% and an accuracy of 97.72%, confirming its suitability for multiclass skin lesion classification.

5. Conclusion

This research demonstrates the effectiveness based on a suggested few-shot learning paradigm incorporating two branches for extraction of important features and an attention mechanism for the classification of skin lesions The adoption of ensemble learning techniques, in particular by means of a Voting Classifier, has resulted in an increase in classification accuracies with winning accuracy and F1 scoring approaches across the seven classes included in the ISIC because the performance of the multiclass classification algorithm on the using the ISIC 2018 dataset archive was on seventy-eight percentile. These results are important for clinical use as appropriate timing of the accurate identification of skin lesions improves the prognosis for the affected patient. This framework makes the case to help escalate this by giving clinicians more powerful tools so that early interventions can be done and hence improve the chances of survivability. Importantly, the models' capacity for effective generalization with few samples trained on is a huge benefit since a general constraint is the difficulty in acquiring large labeled datasets in practice.

Future research will emphasize real-time implementation, validation on diverse populations, and improved learning from limited data. The use of transfer learning to improve classification of rare lesion types. The incorporation of clinical metadata is also expected to strengthen diagnostic performance.

Declarations

Competing Interests

The authors certify that this work does not contain any conflicts of interest.

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Data Availability

The dataset used in the experiment is derived from ISIC 2018 challenge..

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