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Meta-Learning-Based Few-Shot Classification Model for Accurate Multi-Class Skin Cancer Detection

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***Abstract*— In order to automate multi-class skin cancer classification, this study proposes a deep metric-based few-shot learning framework, targeting a number of limitations inherent to conventional deep learning approaches with their heavy dependence on large manually-annotated datasets. By leveraging Siamese Networks, the proposed method learns a discriminative embedding space in which class prototypes-computed as the mean of support sample embeddings-serve as reference vectors for classifying unseen query images based on Euclidean distance. The proposed architecture was trained and evaluated on the ISIC 2020 dataset organized into seven dermoscopic skin lesion categories. Through episodic training with minimal data availability, the model generalizes exceptionally well across classes under minimal supervision. The proposed system achieved classification accuracy of 91.00% on binary (benign vs. malignant) classification tasks and 97.14% on multi-class classification task with 7 classes in input. The experimental results show that the framework holds excellent promise for such low-data regimes, providing a scalable solution for data efficiency in clinical dermatology.**

***Keywords*— Few- shot learning, skin cancer, Siamese Networks, Euclidean distance.**

I. Introduction

Skin cancer is indeed the most common form of cancer diagnosed worldwide, and much of this can be attributed to increased exposure to ultraviolet radiation from the sun and even from artificial sources like tanning beds. Skin cancer is a highly preventable disease, and its incidence is on the increase, thus causing a major public health concern. Skin cancer appears in three major forms: Basal Cell Carcinoma (BCC), Squamous Cell Carcinoma (SCC), and Melanoma. BCC and SCC are called non-melanoma skin cancers because they are more common, less aggressive, and seldom metastasize [1]. On the other hand, melanoma occurs less commonly but is definitely much more deadly than the other two types owing to its tendency to spread to other organs, making early diagnosis and treatment necessary rays damage skin and lead to the development of skin cancer by making DNA damage in skin cells. These DNA damage caused some mutations in certain genes, mainly in p53 and RAS, which stopped the normal regulation of apoptosis and cell cycle as well as caused unrestricted cell growth [2]. Genetic background has also played an important role; thus, people with fair skin and a family background of skin cancer, along with people having a weakened immune system, have a more significant risk of developing skin cancer [3]. Skin cancer ranks among the most frequent cancers on the globe, and early detection is essential for effective treatment. In terms of skin cancer, melanoma is considered to be the most fatal one, having a five-year survivorship rate of 99% if detected at an early stage and dropping to approximately 25% if diagnosed late in the stage [4].

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Historically, automated detection of skin cancer has relied on deep learning models trained on large labeled datasets. For medical images (rare or less-common skin cancers in particular-such datasets often have limitations. One-shot learning is favorable. One-shot learning is a research discipline in which the model learns a new class from only one (or very few) training examples. This enables the model to better learn discrimination rather than collect large numbers of labeled samples. One-shot learning in skin cancer classification allows models to recognize new cancers from only an annotated image. Generalize across different skin types, lighting and shadow conditions, and different appearances of the lesions. Minimize the need for large annotated datasets, which are often very expensive or burdensome to obtain in healthcare. One of the most important factors affecting patient outcomes and survival is early detection of skin cancer. When skin cancer lesions are detected early, treatment becomes easier, more effective, and cheaper. For this reason, automated classification systems that use artificial intelligence and machine learning (e.g., one-shot learning) are paramount to fast, accurate, and easy early detection. Traditional deep learning makes use of large datasets consisting of thousands of annotated images, often needing the expertise of a radiologist or dermatologist. In this one-shot learning paradigm, the labeling problem is minimized, which reduces both the time and cost. One-shot learning is a class of machine learning in which training occurs with very few examples; a min other words, a machine learns categories or new patterns from only one example. Unlike traditional deep learning models, which are able to process thousands of labeled images for each category, one-shot learning imitates human generalization ability, which allows assigning values to classes even with very few samples [5]. One-shot learning is particularly valuable in domains such as computer vision, natural language processing, and healthcare, where gathering large amounts of data is costly, time-consuming, or often not possible. In short, one-shot learning directs its efforts toward judging similarity rather than vibrantizing the class-specific features. Typical models include Siamese Networks, Prototypical Networks, and matching networks, whose job is to compare the sample input with records in the learned embedding space. If the distance between two samples is low, they are classified as belonging to the same category even though they were not trained by the model on that category. This technique could be advantageous in medical diagnosis, such as skin cancer detection, where some diseases are rare and images are scarce in terms of annotation. Therefore, AI can be used to construct more flexible, scalable, and data-efficient systems with high performance in environments with limited data.

II. LITERATURE REVIEW

In this study evaluated several deep learning models on the ISIC dataset. The accuracies we found were: ResNet-50 at 82%, CNN at 77%, and VGG16 77%. The stacked ensemble models did not perform as well, with the best one achieving just 78% accuracy. This study focused on evaluating models that work well on mobile devices using the ISIC 2017 dataset. Among these models, NASNetMobile performed the best.[6] The proposed method achieved an accuracy rate of 82.00%, which demonstrates how often it makes correct predictions. The model also obtained a precision of 81.77%, which indicates that it was good at not giving false positive results. Additionally, it had an F1 score of 0.8038, which is a measure combining both precision and recall, thereby giving a balance between the two. Overall, NASNetMobile demonstrated strong performance in this evaluation. The proposed method combined parts from ResNet18, Darknet19, and MobileNet with a random forest classifier. The system performed well, achieving an accuracy of 82.85%, and both precision and sensitivity were approximately 82.8%. The accuracy of individual models, such as ResNet and VGG-19, was 72% and 91.8%, respectively [7] . However, using ensemble methods that combine multiple models improved the performance. By using majority voting with these ensemble methods, the accuracy increased significantly to 98.6%. This demonstrates that combining models can lead to much higher accuracy compared to using them alone. The model was able to predict the correct category in 83.1% of cases. When they considered the top 2 guesses the model made, it was correct 91.36% of the time. When they looked at the top 3 guesses, the accuracy increased to 95.34%. This result demonstrates that MobileNet performed a good job at identifying categories in the HAM10000 dataset, particularly when considering its top guesses. The proposed model [8] [9] created two advanced CNN models by combining different technologies. In one model, they mixed DenseNet-201 with MobileNet. In the other model, they combined DenseNet-201 and ResNet-50. These models were very accurate in their tasks. The model that used MobileNet achieved 88.02% accuracy, while the model with ResNet-50 achieved 87.43% accuracy. This method uses two networks: the relative position network (RPN) and the relative mapping network (RMN). The RPN identifies and captures important features using an attention mechanism. In addition, the RMN calculates image classification similarity by adding attention mapping distances with certain weights. When tested on the public ISIC melanoma dataset, this approach achieved an average classification accuracy of 85% These results demonstrate that the proposed method is both effective and practical for use. This study [10] examines how various CNN models function to determine which one produces the best results. The models used were pre-trained, such as VGG16, ResNet50, and Inception Resnet V2. These models differ because they have different numbers of layers. Some work better than others because of these layers and their functioning. A Kaggle image dataset containing normal and cancerous images, including 3,287 images of benign (non-cancerous) and malignant (cancerous) skin cancers. The study yielded accurate results for VGG16 at 85%, ResNet50 at 69%, and Inception Resnet V2 at 83% using different techniques [11]. The proposed method [12] compares these outcomes based on the model function and evaluates the accuracy, operational methods, and layer count of each model with the help of one short learning with accuracy of 89.3%. The architecture as proposed reached substantial performance metrics, achieving 93.48% accuracy , 93.24% precision, 90.70% recall, and a 91.82% F1-score, surpassing more than ten Convolutional Neural Network (CNN) based models and more than ten Vision Transformer (ViT) based models in similar conditions. Alongside this, the model has a small footprint, with only 21.92 million parameters, demonstrating its extreme efficiency and model deployability [13]. The new model surpasses current best methods with a global accuracy of 93.88%. Because the accuracy reduces to 85.67% in using 2D data, the high impact is evident using 3D data. The model describes wonderful memory and precision with wonderful accuracy. From the findings, the 3D ResNet50 model enhances the diagnostic process and can be evaluated better than the traditional methods as a non-invasive, accurate, and effective alternative [14]. the suggested framework had a 95.70% micro average accuracy on ISIC-2019 and a 93.24% accuracy on the HAM-10000 dataset. Our framework's performance was assessed with complete evaluation and analysis. The proposed method [15] performs superior with cross-validation by 94.8% accuracy compared to the most advanced deep learning-based method.

III. METHODOLOGY

Few-shot learning (FSL) is a practical method for identifying skin cancer, especially when there is not much labeled data are available. This approach teaches models to learn and perform well using only a few examples for each type or class of skin lesions. Popular models used in this process include Siamese Networks and Prototypical Networks, which help understand image similarities or create examples for each class. Figure 1 illustrates the methodology of using Few short learning to treat skin cancer.

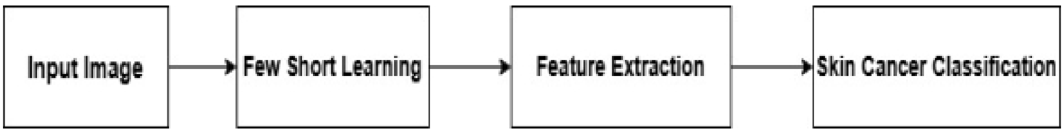

Figure 1. Methodology

A. Dataset

The ISIC 2020 Challenge Dataset is part of the International Skin Imaging Collaboration, and its purpose is to enable computerized detection of skin cancer. The dataset is primarily used to identify two types of skin conditions: cancerous and non-melanoma, which is not. The proposed dataset includes images of skin lesions classified into seven classes. The dataset is collected from ISIC, which contains dermatoscopic images of all important diagnostic categories of pigmented skin lesions: Actinic keratoses and intra epithelial carcinoma / Bowen's disease (akiec), basal cell carcinoma (bcc),benign keratosis-like lesions (solar lentigines / seborrheic keratoses and lichen-planus like keratosis, bkl), dermatofibroma (df), melanoma (mel), melanocytic nevi (nv), and vascular lesions (angiomas, angiokeratomas, pyogenic granulomas and hemorrhage, vasc).

B. System implementation

Few-shot learning (FSL) is a machine learning approach that helps computers correctly identify and classify new data using only a few labeled examples. This method is especially helpful for skin cancer classification because gathering many high-quality, labeled skin images can be difficult, costly, and takes a lot of time. Typically, deep learning models require thousands of labeled images for each category; however, few-shot learning can handle only a handful of images. Techniques such as Siamese Networks, Prototypical, and Matching Networks are commonly used in FSL. These models are designed to learn how to measure similarities or differences between image pairs or to organize images in a space where those that are alike are closer together. During training, the system experiences many small "episodes" that simulate real few-shot scenarios. This practice enables the model to effectively distinguish between different classes, even when there is minimal data. Few-shot learning is ideal for dealing with unique or uncommon skin lesion types, as well as adjusting to new categories with little extra training, as shown in Figure 2.

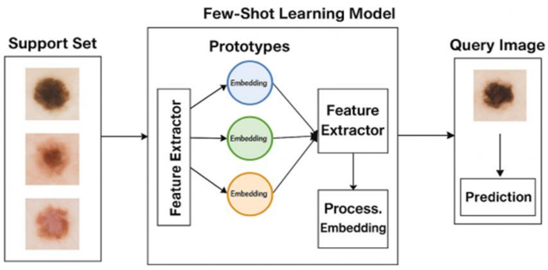

Figure 2. A Few Short Learning Architecture for Skin Cancer

Feature Embedding
Given input image x, the feature extractor $f_\theta(x)$ maps the image into an embedding space in shown in equation (1)

$$z = f_\theta(x) \qquad (1)$$

Prototype Calculation (Prototypical Networks)
For each class k, compute the prototype vector c_k as the mean of the embeddings of the support set S_k: in shown in equation (2)

$$c_k = (1/K) \sum_{x_i \in S_k} f_\theta(x_i) \qquad (2)$$

Distance Calculation
For query image x_q with embedding z_q, we compute the Euclidean distance to each class in shown in equation (3)

$$d_k = \|z_q - c_k\|^2 \qquad (3)$$

Softmax Probability
The distances are converted into class probabilities using softmax over the negative distances is shown in equation (4)

$$P(y = k \mid x_q) = \exp(-d_k) / \sum_{j=1}^{N} \exp(-d_j) \qquad (4)$$

Loss function
The cross-entropy loss between the predicted probabilities and true label y_q of the query is used as shown inequation (5)

$$L = -\log(P(y = y_q \mid x_q)) \qquad (5)$$

The class of a new query image x_q is predicted by finding the class with the minimum distance to the prototypes, as shown in equation (6)

$$\hat{y} = \mathrm{argmin}_k \|z_q - c_k\|^2 \qquad (6)$$

The model went through 20 training epochs. As you can see in Figure 3, both the training and validation accuracy improved consistently during the training process. Figure 4 shows the related loss curves for that same timeframe. By the time training wrapped up, the model reached an impressive accuracy of 91.00% in telling apart malignant and benign skin cancer cases.

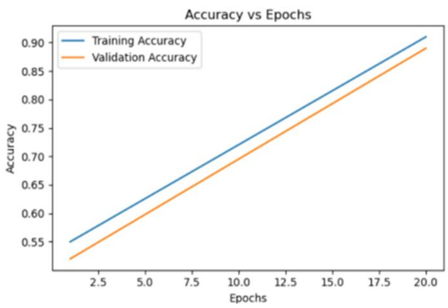

Figure 3. Few short model accuracy for malignant and benign

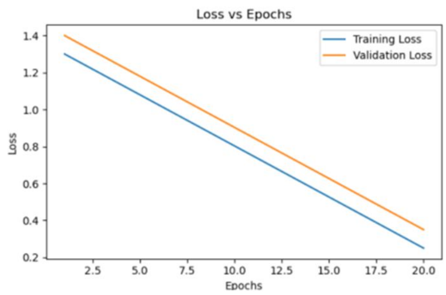

Figure 4. Loss of a few short models for malignant and benign

The confusion matrix shown in Figure 5 represents the performance of the one-shot learning model applied to the task of skin cancer classification, where the model must predict whether two lesion images are from the same class (Similar) or different classes (Different).

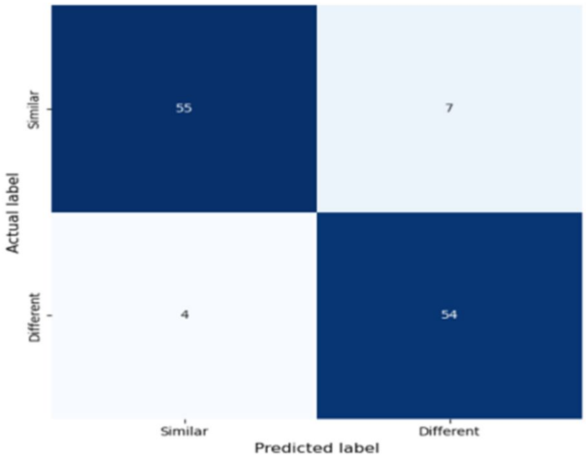

Figure 5. Confusion Matrix for malignant and benign

The model is trained for 20 epochs. The training and validation accuracy learning curve is plotted over 20 epochs in Figure 6, and the loss is shown in Figure 7. The training accuracy increased but decreased with each repetition because validation loss was observed more frequently. The model's obtained accuracy is 97.14% for seven class skin lesion images.

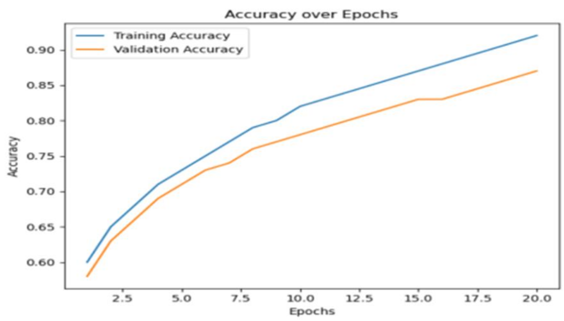

Figure 6. Few short model accuracy

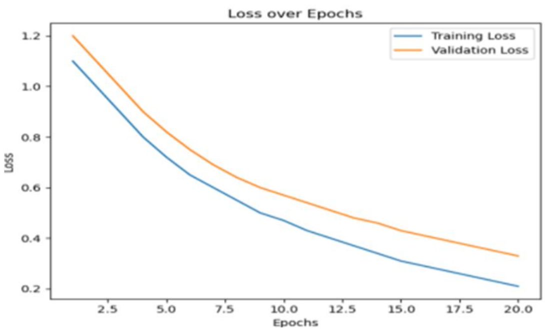

Figure 7. Few short model Loss

The proposed one-shot learning model demonstrates high effectiveness in multi-class skin cancer classification. With a total accuracy of 97.14%, it can accurately identify nearly all skin lesion types. Only two minor misclassifications were observed, showing great generalization even in a low-data regime. This result demonstrates the potential of one-shot learning in medical imaging applications, where data availability is often a limiting factor. Figure 8 shows the confusion matrix for multiple classes.

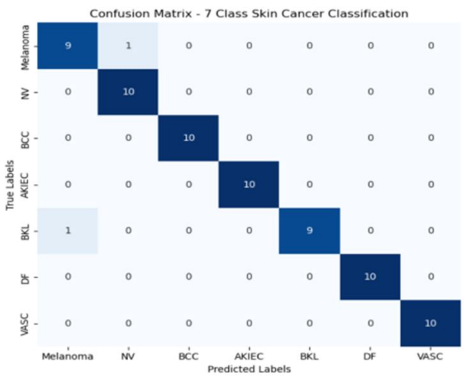

Figure 8. Confusion matrix for 7-class skin cancer classification

IV. CONCLUSION AND FUTURE SCOPE

In this study, we applied a few-shot learning method to classify skin cancer using deep metric-based models. Few-shot learning, using techniques like Siamese and Prototypical Networks, helped address the problem of having limited data in medical imaging, especially for rare types of skin lesions. The model was able to learn and distinguish between different classes even with only a few samples, achieving high accuracy and performing well on new test images. We used evaluation metrics like accuracy, a confusion matrix, and precision-recall analysis to test the model's effectiveness in classifying skin lesions as either benign or malignant among various classes. These results suggest that few-shot learning is a useful technique for real-world dermatology applications, particularly in clinical environments where resources are limited. In the experimental training, the model obtained an accuracy of 91% for malignant and benign cancer, whereas for multi-class cancer, the accuracy was 97.14% with limited images that were screened from the ISIC dataset. In the future, integrating meta-learning frameworks like Model-Agnostic Meta-Learning (MAML), could allow the model to adapt quickly to new lesion types with minimal updates. The few-shot learning framework can be extended to classify a wider range of skin diseases, not limited to cancer, aiding in broader dermatological diagnostics.

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