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Few-Shot Learning Approach To Acne Classification

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ABSTRACT: Acne is a common skin condition that affects people worldwide. Correctly identifying acne types is crucial in prescribing and developing effective treatments. However, traditional classification of acne by a dermatologist is subjective, time-consuming, and not widely accessible. To address this problem, in this paper, we propose a novel machine learning approach that achieved an impressive 91.75% accuracy in acne classification, even in a low-data scenario, using Few-shot learning (FSL) techniques. FSL is a type of machine learning designed for low-data scenarios. The FSL approach was implemented using Prototypical Networks, which utilize pre-trained CNN models to generate embeddings for the acne samples. We experimented with various CNN models in order to determine which would produce the highest accuracy. This was the GoogLeNet model. The results were compared against the performance of pre-trained CNN models and a CNN-established baseline for evaluation. The FSL approach outperformed current state-of-the-art models by 35.12% (compared to a CNN baseline) and 15.19% (compared to a pre-trained CNN model). The high accuracy achieved by this FSL approach to classifying acne shows potential of being integrated in an app or other medical systems to aid patient diagnosis by enhancing accessibility, and dermatologist diagnosis accuracy and efficiency.
KEYWORDS: Robotics And Intelligent Machines, Machine Learning, Acne, Image classification, Few-shot learning (FSL), Prototypical Network, Convolutional Neural Network (CNN), Diagnosis.

Introduction

Acne vulgaris (Acne) is the one of the most prevalent diseases in the world, affecting approximately 80% of adolescents and 40% of the global population.[1] There are 6 different types of acne, each type requiring different treatments. Correctly identifying acne type would help in prescribing and developing the most appropriate and effective treatments to the specific type of acne that is present.[2] If acne is incorrectly diagnosed, individuals may receive ineffective treatments, leading to prolonged symptoms, potential worsening of the condition, and negative impacts on their quality of life.[3] Traditionally, types of acne are identified through visual inspection and using clinical knowledge by dermatologists and healthcare professionals.[4] However, this method of categorizing acne types is subjective and time-consuming.[5] Additionally, not everyone suffering from acne has the resources to visit a healthcare professional to diagnose their acne.

The primary objective of this research is to develop and evaluate a computational approach for classifying acne types using machine learning techniques. Advancing traditional fields such as medicine and dermatology through innovative approaches, such as artificial intelligence and telemedicine, is essential in improving diagnostic accuracy, speeding up patient care, accelerating research and making healthcare more accessible and cost-effective.[6]

To address current limitations of the traditional method of acne classification by clinical inspection, this study introduces an efficient, accessible and accurate few shot learning-based approach. Few-shot learning (FSL) is a sub-discipline of machine learning, which improves AI models' accuracy and performance when there is a limited amount of labeled data.[7] More commonly used CNN-based approaches, on the other hand, require large quantities of labeled data to perform well and avoid overfitting. There is a lack of good quality, labeled, public datasets of acne images, which can be attributed to the privacy concerns, labeling complexities, and resource constraints regarding this classification problem.[8] Therefore, we propose that FSL will provide a promising and suitable new approach to a more objective, efficient and accurate method of acne classification.

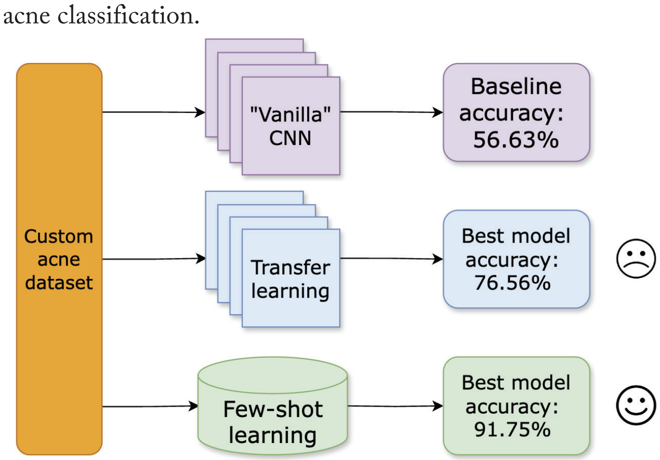

Figure 1: Summary of methodology and results.

The methodology of this research seeks to investigate machine learning approaches for acne classification. Transfer learning using pre-trained CNN models and Prototypical Networks, a commonly used architecture in FSL, will be compared against a baseline in order to determine its effectiveness in this classification problem, as shown in Figure 1. Our methodology lends itself to answer the following questions:

1. How does the baseline approach perform?
2. How can we apply a second-level transfer learning approach to enhance model performance by addressing the limitations of a simple baseline architecture?
3. How does FSL outperform other methods by addressing the problem of limited data?

By systematically investigating various neural networks and adapting FSL techniques to our dataset, we are the first to develop an FSL-based end-to-end framework that accurately classifies acne types using minimal labeled data. By leveraging advanced machine learning techniques to achieve improved classification accuracy, patients can receive faster and more reliable diagnoses, leading to timely and effective treatments. The use of a computational alternative to acne classification makes diagnosis more accessible, and may also be able to reduce the current workload on dermatologists, leading to cost savings, improved resource allocation, and better overall healthcare delivery.[6]

Related Work

Recently, the field of computer vision has been developing rapidly, with areas such as object detection, feature extraction and image analysis seeing significant improvements. These developments have assisted the growing use of machine learning techniques in dermatology, with computer-aided diagnosis (CAD) emerging as a promising, accurate and efficient method of medical diagnosis. This section first discusses the general use of machine learning then few-shot learning and finally Prototypical Networks in dermatology.

Machine Learning in dermatology:

Machine Learning in dermatology, especially the use of convolutional neural networks (CNNs), has been extensively researched for diagnosing skin conditions. Alamdari *et al.*[9] proposed a two-level k-means clustering method to improve image segmentation accuracy by 70%, achieving 100% accuracy in distinguishing acne from non-acne skin using fuzzy c-means clustering, and 80% and 66.6% accuracy in distinguishing acne scars from active lesions using FCM and SVM, respectively. Junayed *et al.*[10] developed a CNN model based on Deep Residual Neural Network with 47 layers, achieving 95.89% accuracy in classifying acne into five types. Naidu *et al.*[11] used a custom dataset combining Kaggle and private data to train models like VGG-16, XCeption, and Inception V3, yielding validation accuracies of 68.4%, 76.03%, and 89.39%. Haenssle *et al.*[12] compared Google's Inception v4 CNN with dermatologists in identifying melanoma, where the CNN outperformed dermatologists with a sensitivity of 82.5%. Lilhore *et al.*[13] integrated Hybrid U-Net and MobileNet-V3 features, optimized via Bayesian methods, achieving 98.86% accuracy in diagnosing skin cancer on the HAM-10000 dataset, surpassing models like MobileNet and VGG-16.

Few-shot Learning:

In 2024, Özdemir *et al.*[14] combined few-shot learning with transfer learning to enhance rare skin disease classification on datasets like ISIC2018, with data augmentation further improving performance. Chen *et al.*[15] introduced CDD-Net, a few-shot learning method with context feature fusion, achieving a 9.14 percentage point improvement in skin disease classification accuracy on the new Derm104 dataset. Ye *et al.*[16] proposed FEAT, improving few-shot learning through instance embedding adaptation using Transformers, achieving state-of-the-art results on two benchmarks and excelling in extended tasks. Mahajan *et al.*[17] developed Meta-Derm-Diagnosis using meta-learning techniques like Reptile and Prototypical networks, outperforming conventional methods in skin disease identification on datasets such as ISIC 2018. Wang *et al.*[18] proposed a cross-domain few-shot segmentation framework that improved rare-disease skin lesion segmentation by leveraging learning from common diseases, surpassing existing methods and promoting cross-domain research in the medical field.

Prototypical Networks:

Prototypical Networks, introduced by Snell *et al.*19, are a few-shot learning algorithm that classifies by computing distances to class prototype representations in an embedding space, significantly outperforming previous models and achieving state-of-the-art results on the CU-Birds dataset. Prabhu *et al.*[20] extended this approach with Prototypical Clustering Networks (PCN) for dermatological disease diagnosis, which handled intra-class variability by learning a mixture of prototypes and demonstrated strong few-shot generalization capabilities. Du *et al.*[21] proposed ProtoDiff, incorporating a task-guided diffusion model during meta-training, which significantly improved few-shot learning performance across various domains. Chamarthi *et al.*[22] evaluated Prototypical Networks for skin lesion classification and found improved performance in certain cross-domain scenarios compared to a baseline. Chen[23] enhanced Prototypical Networks with EfficientNet and data augmentation, achieving a ~6% performance increase in 5-way 5-shot learning tasks on CIFAR100. Overall, advancements in computer vision have significantly enhanced machine learning applications in dermatology through the use of CNNs, FSL and Prototypical networks, of which will be further explored in this study.

Preliminaries:

Prototypical Networks:

Prototypical networks are a type of few-shot learning algorithm that make use of class prototypes in an embedding space to classify data. These networks use pre-trained CNN models to extract features from the training images. These features are then fed into a Prototypical Network, which then calculates the embeddings of the images in each class and averages them to produce class embeddings, which are also called class prototypes. A support set, consisting of labeled samples, are used to generate class prototypes, while the query set contains unlabeled samples to be classified. When an image from the query set is to be classified, its embeddings are calculated by the CNN model and then mapped non-linearly into an embedding space. Euclidean distance is used to find the distance between the query point and each of the class prototypes, and the query point will be classified as the class of the nearest prototype (see Figure 2).[19]

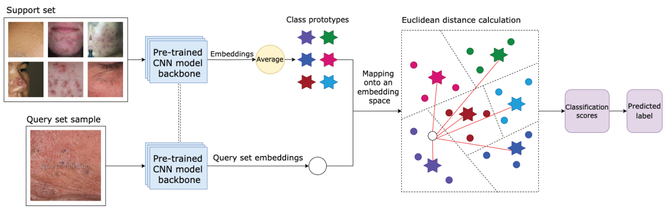

Figure 2: Prototypical Network.

Transfer Learning:

Transfer learning is applied in this study both within Prototypical Networks, which use pre-trained models for feature extraction, and through a second-level approach, where pre-trained models are used to evaluate traditional CNN-based image classification. This involves reusing knowledge from a prior task to improve performance on a related task.[24]

■ Methodology

Dataset:

Due to the lack of large, well-balanced public datasets with data for all the types of acne, we created a custom dataset to include all the 6 different types: whiteheads, blackheads, papules, pustules, nodules and cysts. The images were sourced from DermNet and an open source dataset "acnes-xf7ez_dataset".[25,26] DermNet is a clinical resource website about dermatology and skin conditions, and all images sourced from DermNet have been reviewed by dermatologists.[25] The sources used to collect images for the various acne types are as follows:

- Whiteheads: Sourced primarily from a DermNet, supplemented with additional images from acnes-xf7ez_dataset
- Blackheads, pustules, and cysts: Sourced from DermNet
- Nodules and papules: Sourced primarily from acnes-xf7ez_dataset

Overall, this custom dataset contains 540 images with at least 30 images for each type. We then split this custom dataset into training and testing by a 75/25 validation split, and the class distribution of the training dataset (support set) and testing dataset (query set) can be seen in Figure 3. All images were preprocessed by resizing, changing aspect ratio, ensuring uniform quality and resolution.

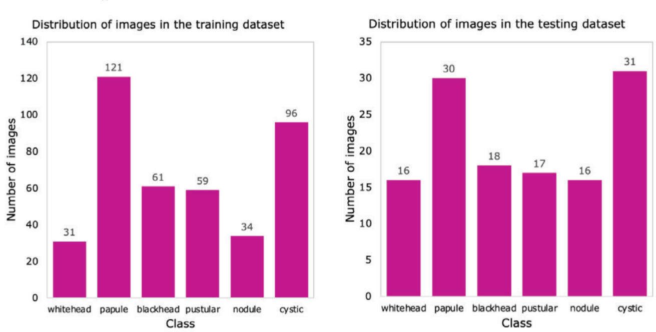

Figure 3: Distribution of images in the training and testing dataset.

Baseline CNN-based approach:

Convolutional neural networks (CNNs) are a commonly used approach when handling image classification problems. Therefore, we will use a "vanilla" CNN to determine a baseline accuracy for this image classification task. In this study, we designed a "vanilla" CNN from scratch. This architecture represents the simplest form of a CNN, without any additional complexities or modifications (Figure 4). It was made by importing layers from the Keras library.[27] The simple architecture of a vanilla CNN helps establish a solid performance benchmark that more complex models can be compared against, allowing effective analysis of any improvements that enhancements and additions in layers offer. The effectiveness of CNNs as a valid baseline has been demonstrated in a study by Shin *et al.*[28] and another study by Razavian *et al.*[29], where the CNN-SVM baseline outperformed other non-CNN baselines.

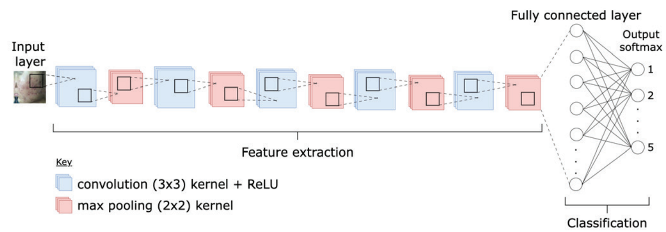

Figure 4: Our "vanilla" CNN architecture.

Second-level transfer learning approach:

We explored a second-level CNN-based approach using pre-trained CNN models, also known as transfer learning. We retrained pre-trained models on the custom dataset, including VGG16, VGG19, InceptionV3, EfficientNet, and ResNet50.[30-33] The models were imported and initialized with the pre-trained weights from the ImageNet dataset.[34] To retain the learned features, we froze the layers of the pre-trained models, preventing their weights from being destroyed or overwritten during retraining. To adapt these models for our specific task, we added new trainable layers on top of the frozen layers. For every pre-trained model that was retrained, the following layers were added

- GlobalAveragePooling2D() - to reduce the spatial dimensions of the feature maps
- Dense(1024, activation='relu')(x) - to introduce non-linearity
- Dropout(0.5)(x) - to prevent overfitting
- Dense(6, activation='softmax')(x) - to produce 6 class probabilities for each class

We compiled each retrained model using the Adam optimizer and the categorical cross-entropy loss function, ensuring efficient training and robust performance. When each model was being fitted, we experimented with the number of epochs to find the one that produced the best validation accuracies for each model.

Few Shot Learning-based approach:

In order to test our hypothesis that FSL will outperform the CNN-models in the context of our small, imbalanced dataset, we adopted an FSL-based approach using Prototypical Networks. With a simple inductive bias, Prototypical Networks demonstrate high effectiveness in handling small and imbalanced datasets.[19] Additionally, its simplistic approach to FSL allows for less complex training and higher efficiency over

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other FSL approaches, such as MAML, which would be necessary for this image classification task.[19]

Prototypical networks leverage pre-trained CNN models as a backbone to extract features from images and transform them into feature vectors, or embeddings (See Preliminaries). Therefore, we experimented with different popular and high-performing CNN models, including GoogLeNet, ResNet18, VGG-16, ResNet50, EfficientNetB0, and AlexNet, in order to identify the ones that will produce the highest accuracy.[30,32,33,35,36]

After identifying the CNN model that produced the highest accuracy, we experimented with changing key parameters to optimize the performance of the Prototypical Network. These parameters included:

- The number of examples per class provided in the support set (N-SHOT)
- The number of query examples per class used to evaluate the model (N-QUERY)
- The number of training episodes (N_TRAINING_EPISODES)

The Prototypical Network was implemented using the EasyFSL library.[37]

Results

In this section, we demonstrate the effectiveness of the methods we have investigated by comparing their classification accuracies against a baseline. We used two machine learning classification methods—CNNs and Prototypical Networks—to classify acne. We conducted experiments on our custom acne dataset using a 75/25 split for both CNNs and the Prototypical Network and measured their classification accuracies using metrics like accuracy, precision, recall, and F1 scores.

Our problem formulation and analysis lends itself to answer the following questions stated in the

introduction:

1. How does the baseline approach perform?

2. How can we apply a second-level transfer learning approach to enhance model performance by addressing the limitations of a simple baseline architecture?

3. How does FSL outperform other methods by addressing the problem of limited data?

Baseline approach:

In Figure 4, the "vanilla" CNN architecture we used to establish a baseline accuracy to be able to compare later results is shown. This achieved an accuracy of 56.63%, indicating that the classification problem is not too complex and that there is room for improvement by utilizing more advanced techniques.

Results from second-level approach:

The ability of pre-trained models to utilize the knowledge learned when trained on large datasets allows them to achieve a higher accuracy compared to the baseline despite the small size of the dataset. However, since the dataset is also imbalanced, the second-level approach did not achieve validation accuracies exceeding 77%, demonstrating inadequate performance.

As seen from the results in Figure 5, the InceptionV3 and VGG16 models achieved the highest validation accuracy of 76.56%. This suggests that they were able to generalize relatively well on the data. Unfortunately, the ResNet50 and EfficientNet models achieved accuracies below the baseline. However, the disparity between InceptionV3's high training accuracy and significantly lower validation accuracy indicates a degree of overfitting, which is common for small datasets such as ours.

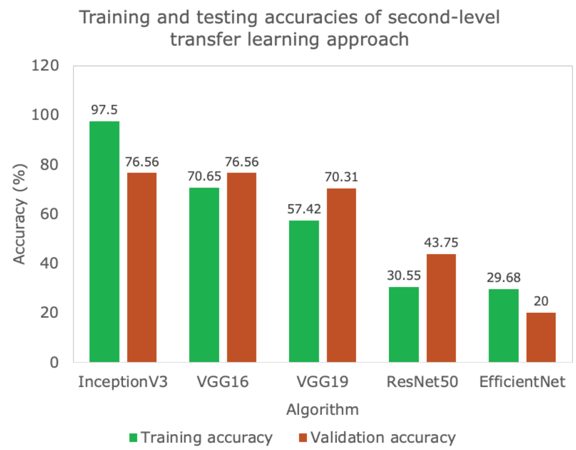

Figure 5: Training and testing accuracies of second-level transfer learning approach

InceptionV3, VGG16 and VGG19 all out-performed the baseline model and achieved validation accuracies over 70%. The InceptionV3 model is able to reduce the number of parameters by breaking down larger convolutional layers into smaller ones. This could explain why it had a higher validation accuracy compared to the other models, despite the small dataset it was trained on.[38]

A study by Salinas *et al*.[39] shows that expert dermatologists achieve a sensitivity rate of 84.2%. Since the results of our second-level approach are lower than this, this approach would not be able to complement dermatologists when classifying types of acne.

Results from FSL approach:

The second-level approach using pre-trained CNN models did achieve results exceeding the baseline in most cases. However, they were limited in their performance due to the large class imbalance and small size of our dataset. Therefore, more experiments were conducted using Prototypical Networks.

We experimented with various pre-trained CNN models as the backbone of our Prototypical Network in a 6-way 10-shot scenario with 5 query points per class. It was found that the model using GoogLeNet as its backbone achieved the highest accuracy (Table 1). GoogLeNet follows the Inception architecture, similarly to the InceptionV3 model in the second-level approach, which may explain why it outperformed all other models.

Table 1: Performance of Prototypical Networks with different CNN models.

CNN model backbone	N_SHOT	N_QUERY	N_TRAINING _EPISODES	Accuracy / %	Precision / %	Recall / %	F1 / %
AlexNet	10	5	150	50.00	50.03	50.00	49.97
VGG16	10	5	150	25.00	6.25	25.00	10.00
ResNet18	10	5	150	81.50	81.83	81.50	81.50
ResNet50	10	5	150	84.00	84.64	84.00	84.14
EfficientNetB0	10	5	150	81.25	81.13	81.25	81.10
GoogLeNet	**10**	**5**	**150**	**91.75**	**91.86**	**91.75**	**91.76**
GoogLeNet	8	7	150	87.32	87.38	87.32	87.31
GoogLeNet	12	3	150	87.50	87.52	87.50	87.47
GoogLeNet	10	5	200	86.75	86.75	86.75	86.74

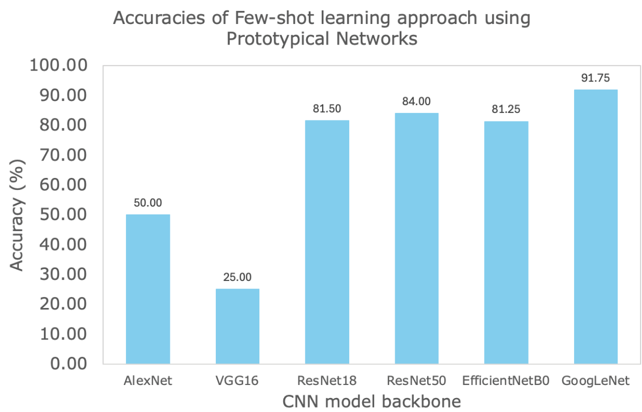

Figure 6: Accuracies of Few-shot learning approach using Prototypical Networks.

After identifying GoogLeNet as the best performing backbone, the parameters (N_SHOT, N_QUERY and N_TRAINING_EPISODES) were adjusted to establish the best performing configuration. This was the Prototypical Network in a 10-shot scenario with 5 query points per class and 150 training episodes (Table 2).

Table 2: Performance of Prototypical Networks with GoogLeNet backbone.

CNN model backbone	N_SHOT	N_QUERY	N_TRAINING_EPISODES	Accuracy / %	Precision / %	Recall / %	F1 / %
GoogLeNet	**10**	**5**	**150**	**91.75**	**91.86**	**91.75**	**91.76**
	8	7	150	87.32	87.38	87.32	87.31
	12	3	150	87.50	87.52	87.50	87.47
	10	5	200	86.75	86.75	86.75	86.74

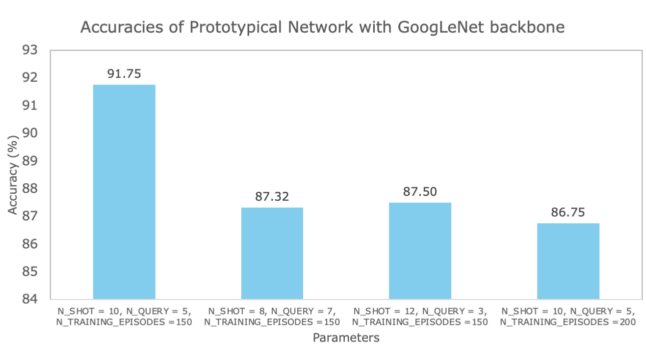

Figure 7: Accuracies of Prototypical Network with GoogLeNet backbone.

N_SHOT and N_QUERY must add up to 15 due to the limitations of our small dataset.

- When increasing N_QUERY to 7 and decreasing N_SHOT to 8, accuracy decreased. This is due to having fewer support samples to effectively compare against a higher number of query points.
- When decreasing N_QUERY to 3 and increasing N_SHOT to 12, accuracy remained higher than the previous configuration but still decreased slightly. This is due to the Prototypical Network having fewer query points to evaluate the model.
- Increasing the number of training episodes decreased accuracy by 5%. This could be because the model potentially overfitted to the training data, reducing its generalization capability.

Discussion

In this study, we proposed that FSL will provide a promising and suitable new approach to a more objective, efficient and accurate method of acne classification compared to traditional CNN methods. From our results, we observed that FSL, particularly through the use of Prototypical Networks, significantly outperformed transfer learning using pre-trained CNN models (Figure 8), confirming our hypothesis. This success can be largely attributed to the nature of FSL, which is specifically designed to handle tasks with limited data. Similar successes have been observed in other studies, where accuracies exceeding 90% in plant disease recognition were achieved in a low-data scenario using FSL.[40]

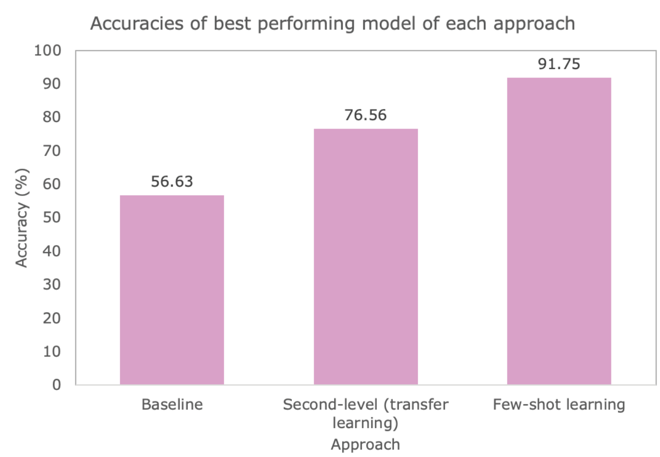

Figure 8: Accuracies of best performing model of each approach.

Our experiments demonstrated that the Prototypical Network using GoogLeNet as its backbone achieved the highest accuracy in our 6-way 10-shot scenario with 5 query points per class (Figure 7). This can be explained by the Inception architecture's efficiency in feature extraction, which is crucial when dealing with small datasets. By breaking down larger convolutional layers into smaller ones, Inception-based models like GoogLeNet and InceptionV3 can effectively reduce the number of parameters, which likely contributed to their better performance in comparison to other models in their respective approaches.[38]

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Traditional CNNs, although powerful, require large amounts of data to generalize effectively and achieve high accuracy.[41] Since our custom acne dataset is both small and imbalanced, the CNN models struggled to achieve high validation accuracies without overfitting. On the other hand, FSL approaches, such as Prototypical Networks, excel in low-data scenarios as they construct an embedding space where classification can be performed by computing Euclidean distances to prototype representations of each class.[19]

Future work

To extend this study, the integration of multimodal learning and generative AI, combined with few-shot learning (FSL), presents a promising direction. Due to the performance of Prototypical Networks exceeding that of traditional CNNs in low-data scenarios, integrating additional data modalities by the use of Large Language Models (LLMs) alongside FSL could enhance the understanding and classification of acne types by leveraging text-based data such as patient history, treatment responses, and clinical notes, in addition to image data. This would provide a more holistic approach that considers various different types of patient data, leading to more accurate and personalized dermatological diagnoses.

Furthermore, collaboration with hospitals, clinics and other researchers could help scale the project. They could contribute by providing images of various acne types in order to expand the current dataset and they could also share patient data in order to create multimodal datasets, which include not only images but also clinical metadata. By doing so, we can collectively address the challenges posed by limited data and improve the accuracy, efficiency, and accessibility of medical diagnoses. However, the question of what the challenges are, if any, in scaling FSL approaches to broader, more diverse datasets arises.

Conclusion

Acne presents itself as a significant global health issue due to its high prevalence and significant effects on mental health. While current approaches to acne diagnosis are not highly accessible, subjective and time-consuming, machine learning, particularly the use of Few-shot learning, presents itself as a promising new method of acne diagnosis. A Prototypical Network with a GoogLeNet CNN backbone could be implemented in an app or integrated into medical systems to enhance patient accessibility, accuracy and efficiency of acne diagnosis.

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