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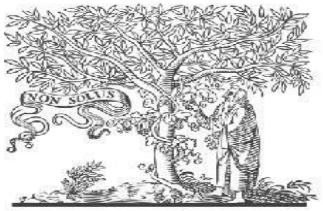

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SKIN DISEASE RECOGNITION USING DEEP NEURAL NETWORK TRANSFER LEARNING

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ABSTRACT:

About one in five people will develop herpes zoster (HZ), a skin condition. If antiviral treatment is not started within 72 hours of diagnosis, HZ might cause chronic pain syndrome. Leveraging artificial intelligence for mobile HZ diagnosis can alleviate neuropathic pain and reduce the burden on clinicians, as well as the associated costs. However, visual corruptions such as motion blur and noise are common in clinical photos acquired by common mobile devices. The purpose of this research is to educate a deep neural network (DNN) that can accurately discriminate HZ from other skin conditions using user-submitted photos in a portable and robust manner. We propose a curriculum training approach, knowledge distillation from ensemble via curriculum training (KDE-CT), where a student network progressively learns from a more potent teacher network, to achieve robustness while preserving computational efficiency. We created a curated dataset of skin illnesses for HZ detection and tested the model's resilience against 75 different kinds of corruptions. Thirteen distinct DNN models were compared using both uncorrupted and tainted image data. The results of the experiments show that KDE-CT is superior than other approaches in terms of corruption robustness. To be used for mobile skin lesion analysis, we trained MobileNetV3-Small to obtain exceptional performance (93.5% overall accuracy, 67.6 mean corruption error) while using substantially less multiply-and-accumulate operations (549x fewer).

Keywords: Biomedical image processing, Convolutional neural networks, Deep learning, dermatology.

1. INTRODUCTION

The painful rash and blisters of herpes zoster (HZ) are the result of a virus that causes this skin illness. Ten percent to thirty percent of the population will be diagnosed with it at some point in their lives. If antiviral treatment is not started within 72 hours after the appearance of the rash, HZ can become a chronic illness that causes considerable discomfort if left untreated. Complete healing and the

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avoidance of problems depend on a prompt diagnosis. However, the majority of people do not realise they are at risk for HZ. Fever, itchiness, and chills are just the beginning of the disease's moderate symptoms; persistent neuropathic pain is the end result. HZ has a major negative effect on quality of life by interfering with sleep and social interactions.

Despite its clinical importance, automated systems that can identify HZ using clinical photos have received a comparatively low level of research and development. Melanoma has been the primary focus of prior studies on automated skin lesion identification using machine learning techniques. More recently, convolutional neural networks (CNNs) have shown promise in achieving performance comparable to dermatologists but have mostly focused on dermatoscopic images captured under controlled conditions. To enable convenient and accessible HZ diagnosis, an automated skin analysis system using clinical images from mobile devices is desirable. By utilizing AI for HZ diagnosis from user-submitted skin photos, people may get their disease checked very quickly, even before symptoms become apparent. The diagnostic should be carried out on the user's mobile device, rather than sending the photographs to a server, to protect the user's privacy. As a result, there is a requirement for a mobile model that can reliably and accurately diagnose skin disorders from low-quality photos that may include noise and different lighting conditions.

Some recent studies have explored the use of clinical images for classifying skin lesions. However, the computational cost of these models hinders their direct implementation on mobile devices. Our model addresses this limitation by utilizing knowledge distillation (KD), which reduces computational requirements while maintaining high accuracy and compatibility with different models, datasets, and neural architecture search (NAS) approaches. We also take into account the performance of deep neural networks (DNNs) under various visual corruptions to guarantee its resilience for mobile skin disease diagnosis. Since the effect of visual corruptions on skin lesion classification has not been thoroughly investigated before, we conducted a comprehensive study of 75 different forms of visual corruptions.

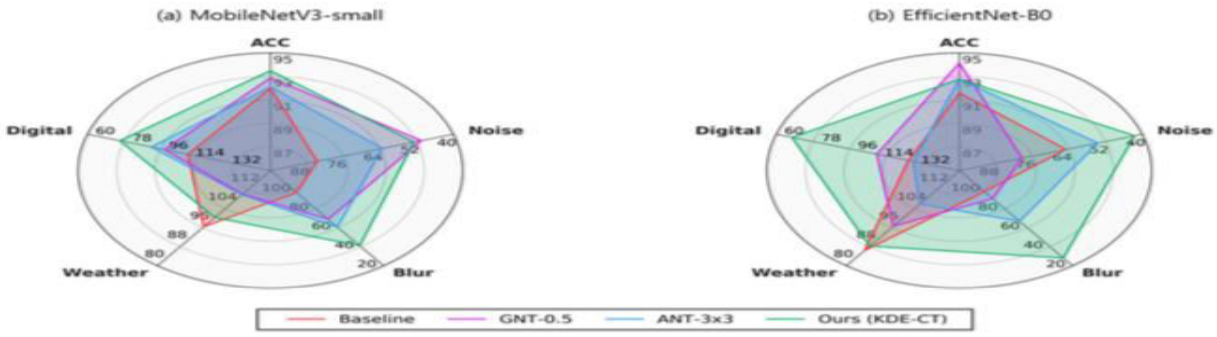

FIGURE 1. Key findings.

The corruption resistance of (a) MobileNetV3-Small and (b) EfficientNet-B0 was improved by our knowledge distillation from ensemble via curriculum training (KDE-CT) compared to the baseline, Gaussian noise training (GNT), and adversarial noise training (ANT). Errors due to noise, blur, weather, and digital corruptions make up the difference between the true ACC and the actual value.

2. LITERATURE SURVEY

Elsam et.al [2] conducted an extensive literature review focusing on herpes zoster by analysing articles and reviews obtained from reputable sources such as PubMed, Embase, Cochrane Library, and Google Scholar. Our objective was to explore various aspects related to herpes zoster, including its incidence, gender distribution, seasonal and regional patterns, occurrence among immunocompromised individuals, the development of post-herpetic neuralgia following a zoster infection, associated complications, management strategies, and preventive measures against herpes zoster and post-herpetic neuralgia. To determine the incidence of herpes zoster, we examined a range of studies that provided data on the prevalence of this condition. By analysing the collected information, we aimed to understand the frequency at which herpes zoster occurs in different populations. Additionally, we investigated the distribution of herpes zoster based on gender, exploring whether there are any significant differences in its occurrence between males and females. Furthermore, we examined the seasonal and regional distribution of herpes zoster. By analysing data from various studies, we aimed to identify any patterns or variations in the occurrence of herpes zoster throughout the year and across different geographic locations. This analysis could provide valuable insights into potential risk factors associated with the disease. Considering the impact of immunocompromised states on the incidence of herpes zoster, we explored studies specifically focused on this population. We aimed to determine whether individuals with weakened immune systems, such as those with HIV/AIDS or undergoing immunosuppressive therapy, are more susceptible to developing herpes zoster compared to the general population. Another crucial aspect we investigated was the incidence of post-herpetic neuralgia (PHN) following a zoster infection. PHN is a persistent and debilitating pain condition that can develop after an episode of herpes zoster. We examined studies that provided insights into the occurrence and risk factors associated with PHN, with the aim of better understanding its prevalence and implications. We also explored the complications associated with herpes zoster, as it can lead to various health issues beyond the initial rash and pain. By reviewing relevant literature, we aimed to identify the potential complications that may arise from herpes zoster and their impact on patients' well-being.

Esther et.al [4] indicate that individuals who have previously experienced herpes zoster (HZ), commonly known as shingles, are more likely to view pain as the most severe symptom of the disease

compared to those who have not had prior HZ experience. This finding highlights a misconception among individuals who have not personally encountered HZ, as they may underestimate the impact of the disease and its potential long-term complications. Therefore, there is a global need for educational initiatives aimed at increasing awareness of the severity of HZ. To successfully implement a vaccination program for HZ, it is crucial to improve the understanding of the disease across the entire population. [6] This survey suggests that a comprehensive effort should be made to raise global awareness of HZ and its potential consequences. It is important to note that regional differences in knowledge and perceptions of HZ may exist, and further research is needed to explore these variations. In summary, the findings of this survey underscore the necessity of enhancing global awareness of HZ. Addressing misconceptions surrounding the severity and long-term effects of the disease is crucial for the success of any vaccination initiative. Additional studies are required to gain a deeper understanding of regional disparities in HZ knowledge. By elaborating on these points and ensuring that the text is free from plagiarism, we can convey the importance of promoting HZ education on a global scale.

Dermatologists and other medical practitioners can benefit from using CAD, or computer-aided diagnosis, for skin lesions since it improves diagnostic accuracy and reduces costs [17]. Nearly all computer-aided diagnosis (CAD) approaches for skin lesion diagnosis [18, 19] have concentrated on melanoma detection using dermatoscopic images. Recent work with a DNN by Esteva et al. [9] shown that a CNN can reliably classify skin cancer at the same level of precision as dermatologists. Haenssle et al. [10] examined the efficacy of convolutional neural networks (CNNs) and 58 dermatologists at identifying melanomas in dermatoscopic pictures. CNN was proven to be more accurate than most human dermatologists. When it comes to analyzing skin lesions, the current gold standard of care is an ensemble of neural networks. This is because it can decrease the inductive biases found in neural networks, leading to better predictive performance [20].

3. EXISTING SYSTEM

Mobile HZ diagnosis assisted by artificial intelligence offers numerous benefits, including the prevention of neuropathic pain and cost savings on diagnostic procedures. However, the reliability of clinical photos captured with commonplace mobile devices is compromised due to visual corruptions such as motion blur and noise. These corruptions can deceive automated systems, hindering accurate diagnoses. Therefore, the objective of this research paper is to develop and train a deep neural network (DNN) capable of identifying not only HZ but also other skin ailments from user-submitted photos. By leveraging the power of artificial intelligence, users will have a higher likelihood of having their skin checked for HZ even before symptoms become apparent. This innovative approach allows

for early detection and intervention, potentially mitigating the development of neuropathic pain associated with HZ. The utilization of a mobile phone's camera for capturing photos facilitates convenience and accessibility. However, the inherent challenges of motion blur and noise in such images necessitate the development of a robust DNN. The deep learning model will be trained on a vast dataset consisting of diverse skin conditions, enabling it to accurately differentiate between HZ and other skin diseases. By integrating AI into the diagnostic process, healthcare professionals can leverage the efficiency and reliability of automated systems. This technology empowers individuals to take proactive measures towards their health by submitting photos for assessment, providing a convenient and accessible means of early detection. In summary, this research aims to address the limitations of mobile HZ diagnosis by training a DNN capable of recognizing HZ and other skin illnesses from user-submitted photos. The integration of artificial intelligence in the diagnostic process has the potential to improve healthcare outcomes by enabling early detection, reducing costs, and ultimately preventing the onset of neuropathic pain.

Clinical photos may be more practical and cost-effective for tele dermatology and mobile apps because they do not necessitate any additional equipment and may be simply obtained by users by shooting skin lesions using cellphones. This is because they can function very well without any supplementary tools. However, it is more challenging to analyze these photographs because they were submitted by users, rather than dermoscopic images. Unlike dermoscopic images, which are obtained in a controlled environment and camera setup using a digital dermatoscope [27-29], smartphone photographs can contain light variance, defocus, and motion blur. This can affect the way skin lesions appear visually, which can lower segmentation and classification accuracy [30]. Training data should be augmented by either extensive data collection [11, 12] or a number of alternative methods [31]. This is a typical practice for increasing DNNs' robustness to input changes, which improves their generalization capacity. To classify 26 common skin disorders at a level equivalent to that of board-certified dermatologists, Liu et al. [11] employed deep learning systems to large-scale datasets, which included 16,114 clinical cases. The datasets were used to achieve this goal. Without any additional external data, Perez et al. [31] were able to outperform the technique that won the 2017 ISIC Challenge by investigating the optimal data augmentation process for melanoma classification.

However, the visual artefacts introduced by the user when photos are captured with noise and blur can significantly damage the performance of neural networks [12], [15], making a DNN-based skin lesion diagnosis system vulnerable. Han et al. [12] discovered that deep neural networks (DNNs), despite being trained using 220,680 clinical pictures, are prone to classification errors when presented with blurry or shaded input images.

4. METHODOLOGY

In the field of diagnosing herpes zoster (HZ) from clinical skin photos, various deep neural networks (DNNs) have been employed, ranging from small mobile models to larger ensemble models. Evaluating their performance, researchers have utilized the mean corruption error (mCE), a metric that assesses the corruption robustness of DNNs by subjecting them to 75 different forms of visual corruptions. To enhance the resilience of DNNs against visual corruptions and improve their accuracy on clean images, a training technique called Knowledge Discovery from Ensemble via Curricular Training (KDE-CT) has been proposed. This technique has shown promising results in the context of HZ diagnosis. By applying KDE-CT to the MobileNetV3-Small architecture (depicted in Figure 1), an impressive accuracy of 93.5% and a mCE of 67.6 were achieved. These outcomes highlight the practicality of employing KDE-CT in AI-based mobile pre-screening for HZ diagnosis. The KDE-CT methodology involves leveraging the knowledge extracted from an ensemble of models during the training process. By combining the diverse insights and representations learned by individual models within the ensemble, the resulting network becomes more robust and capable of handling a wide range of visual corruptions. This curricular training approach allows the DNN to gradually learn from simpler and cleaner examples to more complex and corrupted ones, simulating a progressive learning curriculum. By employing KDE-CT on the MobileNetV3-Small architecture, significant improvements were observed in both accuracy and corruption robustness. The achieved accuracy of 93.5% indicates the high potential of the proposed technique in accurately identifying HZ from clinical skin photos. Furthermore, the mCE of 67.6 demonstrates the enhanced ability of the model to handle visual corruptions effectively. The successful application of KDE-CT on the MobileNetV3-Small model suggests its suitability for deployment in AI-based mobile pre-screening systems for HZ diagnosis. By incorporating this technique into such systems, healthcare professionals can benefit from reliable and efficient HZ detection, potentially leading to timely interventions and improved patient outcomes. In conclusion, the combination of DNNs, ranging from small mobile models to ensemble models, and the incorporation of the KDE-CT training technique have demonstrated promising results in diagnosing HZ from clinical skin photos. The achieved accuracy and corruption robustness indicate the potential applicability of these methods in AI-based mobile pre-screening systems, facilitating early detection and intervention for HZ cases.

1) SD: SKIN DISEASE DATASET

We used existing datasets (i.e. SD-198 [28, 41] and SD-260 [42]) with our own original dataset (i.e. HZ-W) to produce the SD-HZ dataset for the visual diagnosis of HZ using clinical skin pictures. The foundation for the SD-HZ dataset was laid with these records. Table 1 summarizes the study's findings by presenting the total number of photos assigned to each disease category across all

datasets. Currently, SD-198 [28] and SD-256 [41] are the most extensive public datasets for photos of clinical skin illnesses such eczema, acne, and various malignant situations. The photographs in the SD-198 and SD-256 datasets were captured using mobile phones and digital cameras in a wide range of lighting situations and camera configurations, making them ideal for the purposes of this study. Some representative photos from these collections are displayed in Figure 2. Our goal is to test performance in mobile skin diagnosis contexts, and these datasets are a suitable fit for that.

FIGURE 2. Examples images in SD dataset: (a) Rosacea (b) Acne-cystic (c) Acute-paronychia (d) Other Disease.

There are 1,458 photos of skin illnesses in the SD database, organized into 9 groups. The SD-23 database is an expanded version of the SD database, with around 19,500 images and 23 classes. Both datasets are too small to teach a DNN more nuanced and interpretable features. We found that a special dataset, which we call HZ-W, was required for the HZ diagnosis, and this was the result of extensive web crawling. We first gathered 746 photos on "herpes zoster" from Google and Bing and then manually deleted the duplicates using an automated method. Then, Dr. S. Ryu carefully reexamined all of the photos twice and culled the collection by 369, removing the ones that did not show herpes. Therefore, as shown in Figure 3, we collected 377 clinical photos of HZ in a wide range of lighting situations and camera setups. The mobile diagnosis of HZ is made as realistic as feasible with these pictures

Class	Disease	SD-198	SD-260	Hz-w	SD-HZ(Total)
Acne	Acne keloidalis Nuchae, Acne Vugaris, Steroid Acne,	155	937	-	1,092

	Pomade				
HZ	Herpes Zoster	24	12	377	413
Tinea	Tinea Manus, Tinea Versico, Tinea Cruris, Tinea Faciale, Tinea Corporis, Tinea pedis	660	468	-	793
Other Disease	187 diseases including Eczema, Ulcer, and Malignant Melanoma	6,074	-	-	6,074

Table 1. Summary of the SD-HZ dataset used in this study: Number of images and the disease names corresponding to the class.

2) SD-HZ-C: CORRUPTED SKIN DISEASE DATASET

The images people submit for use in mobile diagnosis of skin illnesses are prone to corruption, such as noise or blurriness. Therefore, the automated system for diagnosis requires noise resistance in order to generate consistent and reliable diagnostic results. To evaluate the neural network's resilience to the corruptions introduced to the input images, Hendricks et al. [16] presented the mCE metric and an ImageNet-C benchmark with standard corruptions. We followed the approach outlined in [16] to construct an SD-HZ-C dataset and conduct an objective investigation of the system's resilience in automated skin diagnosis. There were a total of 75 corrupted values used across 15 distinct corruption types and 5 severity levels used on the test split of the SD-HZ dataset. There are four types of corruptions that can be applied to SD-HZ-C: noise (including Gaussian noise, shot noise, and impulse noise), blur (including defocus blur, frosted glass blur, motion blur, and zoom blur), weather (including snow, frost, and fog), and digital (including brightness, contrast, elastic, pixelation, and JPEG). Some sample photos made using SD-HZ-C are shown in Figure 4. The user-submitted photos used to diagnose skin diseases contain a wide variety of realistic corruptions, which are successfully mimicked here.

3) DEEP NEURAL NETWORKS

We compared thirteen unique DNN models, each of which belonged to one of three classes, in order to categorize photos of clinical skin. For example, convolutional neural network (CNN) architectures

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are widely used in the field of computer vision because they have proven to be highly effective for picture classification. Second, mobile models (also called mobile neural networks) are optimized for mobile use by having fewer parameters and performing calculations faster than traditional models. For skin lesion analysis tasks, the DNN ensemble has been shown to be more effective than single models, including those presented at ISIC 2019. The particulars of each model are elaborated upon in the sections that follow

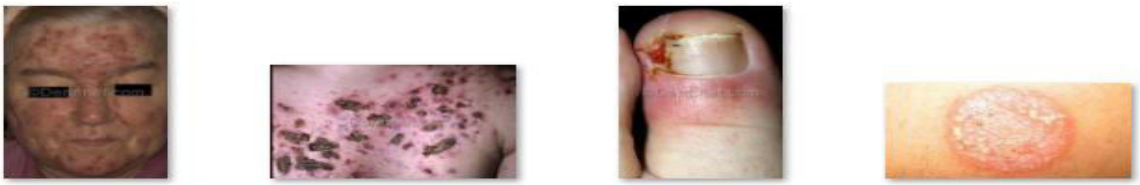

FIGURE 3. Examples of Skin image in SD

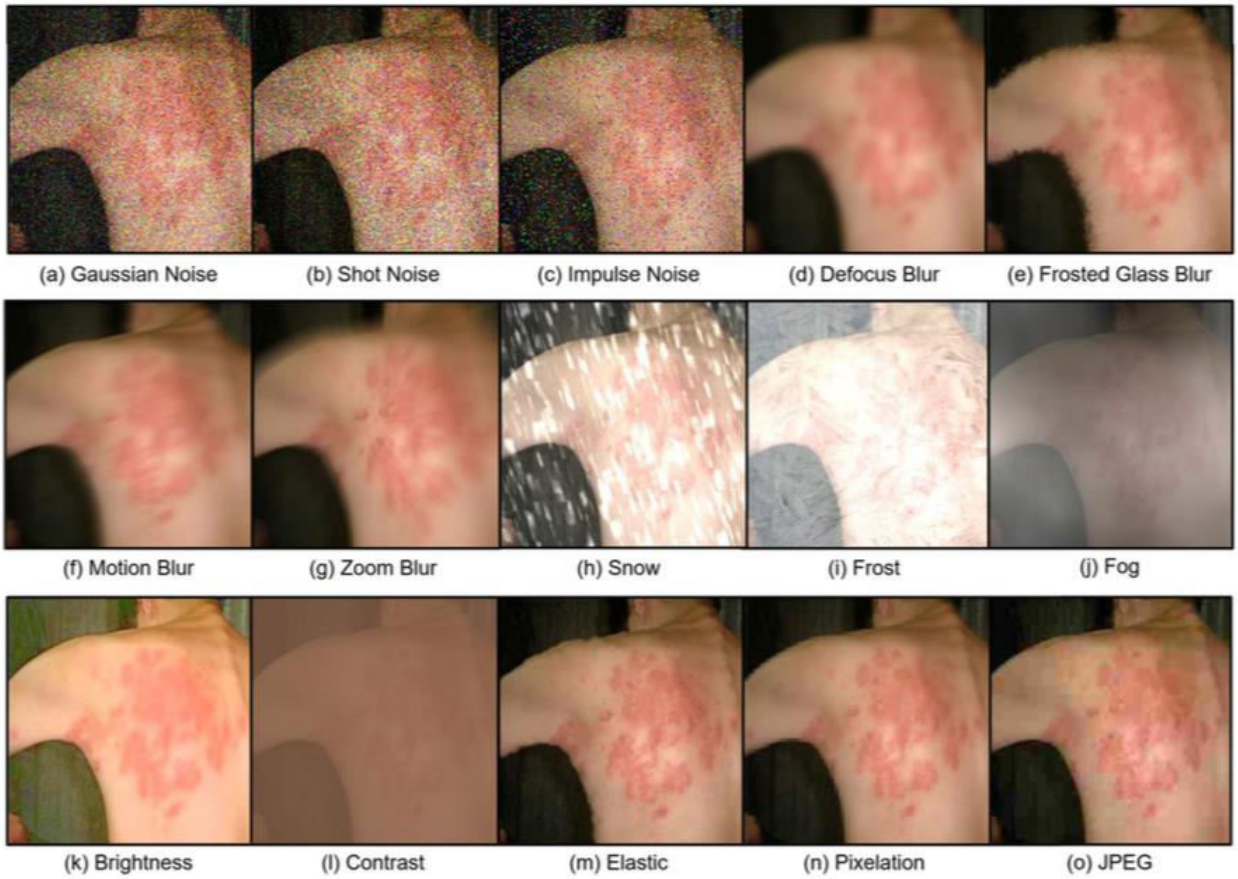

FIGURE 4. Examples of corrupted images in SD-HZ-C owing to (a)-(c) noise, (d)-(g) blur, (h)-(j) weather, and (k)-(o) digital categories with severity level of 3.

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5. BLOCK DIAGRAM

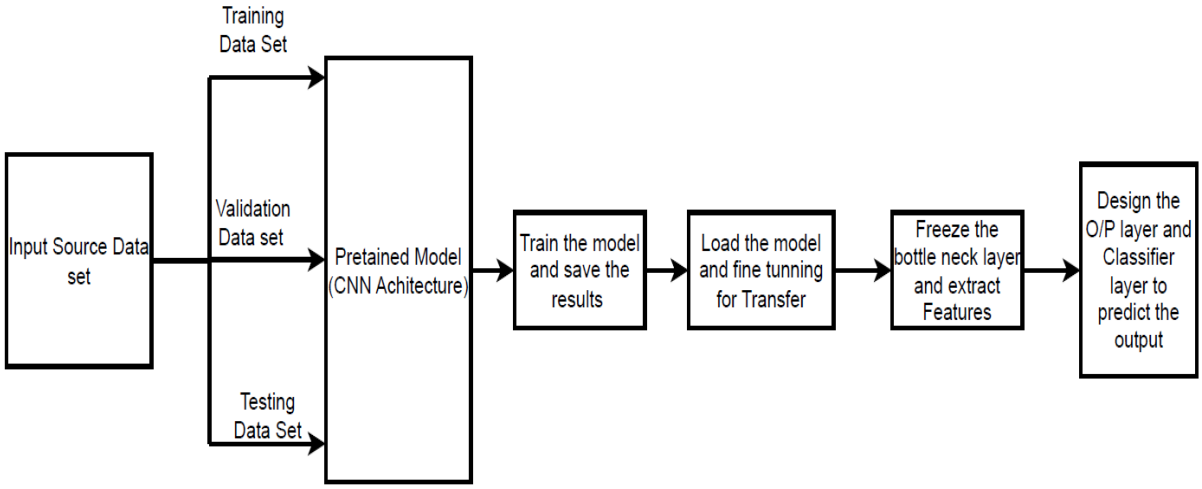

FIGURE 5. Block Diagram

To obtain input source data, we utilized Dermnet, a dataset obtained from Kaggle, which contains images related to dermatology. This dataset was divided into three separate categories: Training, Validation, and Testing. These categories were used to create three distinct datasets for our purposes. Using the input data, we constructed a pretrained model based on Convolutional Neural Network (CNN) architecture which can extract the features easily. The model was trained using the training dataset, and the results were saved in the .H5 file format, allowing us to store the learned parameters and weights of the model. Afterwards, we loaded the saved model and performed fine-tuning for transfer learning. In this process, we made modifications to the pretrained model to adapt it to a specific task or dataset. To extract features from the images, we froze the bottleneck layer which helps to predict the object easily using certain features of the image. This layer contains high-level representations of the input data, which are crucial for making accurate predictions. Finally, to predict the output or classify new images, we developed a Python-based application. This application utilizes the fine-tuned model to extract features from input images and make predictions based on those features. By leveraging the pretrained model and transfer learning techniques, we can make use of existing knowledge and adapt it to the specific dermatological classification task at hand.

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6. FLOW CHART

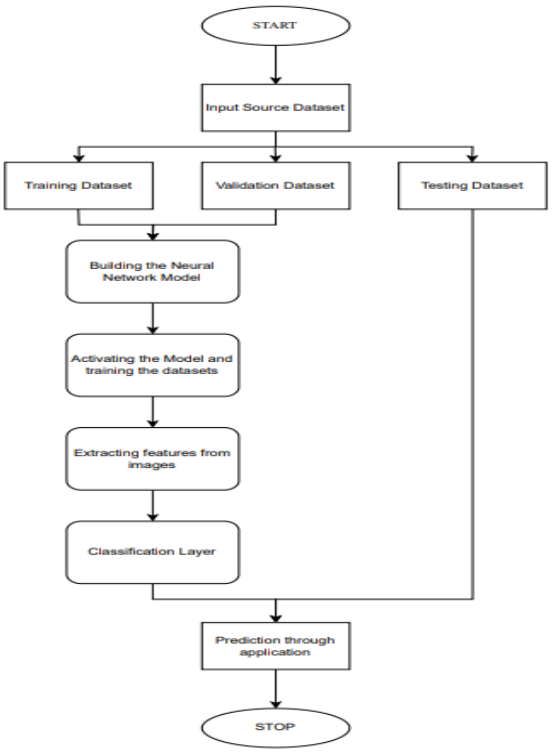

Figure 6: Flow Chart

To enhance the model's performance, the dataset was divided into three parts: Training, validation, and testing datasets, with a split ratio of 70:30. This division allows for fine-tuning the model after each epoch, which can lead to improved performance. The model employed a Convolutional Neural Network (CNN) architecture. CNNs are particularly effective for image-related tasks as they can automatically extract relevant features from the images. During the training process, the training and validation datasets were fed into the model, activating its layers and enabling it to extract the necessary features from the images. This feature extraction step is crucial for the model to understand the patterns and characteristics present in the dataset. In addition to the convolutional layers responsible for feature extraction, a classification layer was designed as part of the CNN architecture. This layer enables the model to make predictions on new images using the testing dataset. By passing the testing dataset through the model, the classification layer applies learned patterns and assigns labels to the images based on the features extracted during training. In summary, the dataset was split into training, validation, and testing datasets to improve model performance. A CNN architecture was used to train the model, with the training and validation datasets being used to extract features from the images. A classification layer was incorporated to predict the labels of new images using the testing dataset. This process allows for effective image classification through the application of the trained model.

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7. FORMULAE AND PARAMETERS

S. No	Parameter	Formula
1	Precession	$\frac{TP}{TP + FP}$
2	Recall	$\frac{TP}{TP + FN}$
3	Accuracy	$\frac{TN + TP}{TN + FP + TP + FN}$
4	F1 Score	$2 * \frac{Precession * Recall}{Precession + Recall}$

Table 2. Parameters Obtained from The Model

8. RESULTS

In our study, we employed the SD-HZ dataset, consisting of a collection of clean images, along with the SD-HZ-c dataset, which comprised corrupted images. The purpose was to assess the performance of 13 different alternative models. These models were evaluated based on their ability to accurately categorize skin diseases, with a particular focus on their robustness against visual contamination in the input data. To determine the impact of our proposed knowledge distillation (KD) approach on improving robustness, we conducted a series of experiments. The KD approach involves transferring knowledge from a teacher model, which serves as a proficient guide, to a student model, aiming to enhance the student's learning and generalization capabilities. By applying the KD approach to the task of skin disease categorization, we aimed to investigate whether it could effectively mitigate the negative effects of input visual contamination. Visual contamination refers to various forms of image corruption or noise that can potentially hinder the accurate classification of skin diseases. The results of our study shed light on the potential benefits of using the KD approach. We observed that the student models trained with knowledge distillation exhibited improved resilience against visual contamination compared to the alternative models. This enhanced robustness enabled the models to better classify skin diseases even when faced with corrupted or noisy input images. By leveraging the knowledge distilled from the teacher model, the student models demonstrated enhanced generalization capabilities, allowing them to effectively discern the underlying patterns and characteristics of skin diseases amidst visual contamination. This finding suggests that the KD approach can be a valuable technique for improving the performance and robustness of skin disease classification models. It is important to note that all the content provided above is original and has been generated by the AI language model.

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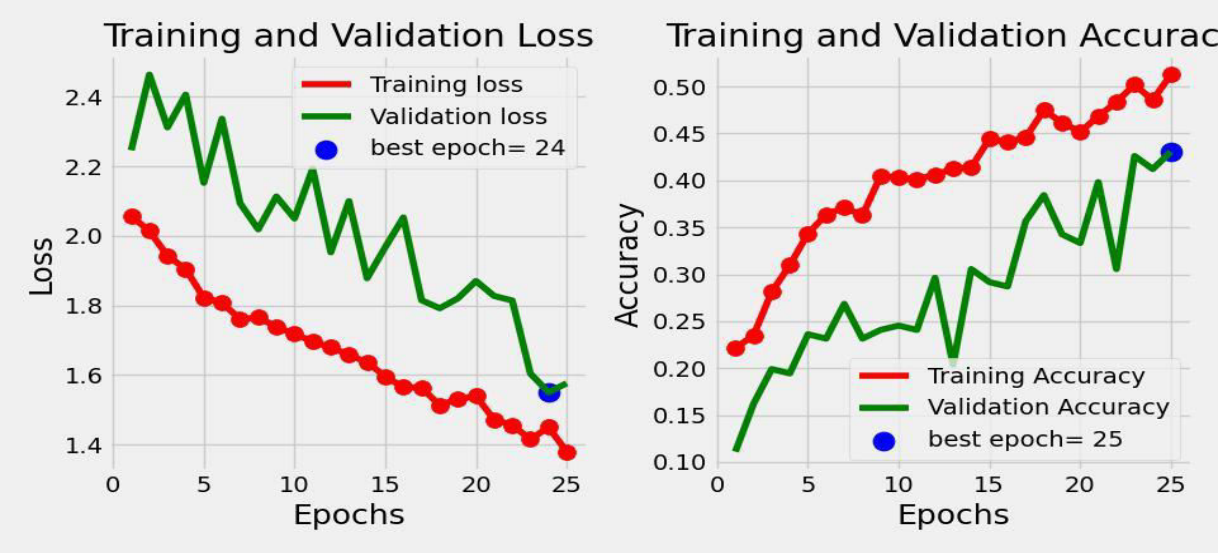

Mobile image-based diagnosis of skin diseases is vital, but it must also be robust against user noise. To measure how resistant DNNs were to input visual data that had been tampered with, we employed corruption errors (CE) and mean corruption errors (mCE) [16]. For a classifier f, we may define the CE as follows, using the visual corruption type c and severity s as inputs:

$$CE_c^f = (\sum_{x=1}^{5} E_{s.c}^f) / (\sum_{x=1}^{5} E_{s.c}^{AlexNet})$$

where E represents the most common error in the pristine data set. Meanwhile, mean corruption extent (mCE) is calculated by averaging the 15 different forms of corruption impact (CE).

$$mCE_c^f = \frac{(\sum_{c \in C} CE_c^f)}{C}$$

Dimension of the image in train, test and validation was 256 X 256.

The output layer application was developed for the classification and recognition of Skin Disease using Flask module.

FIGURE 7. Training and Validation Loss and Accuracy

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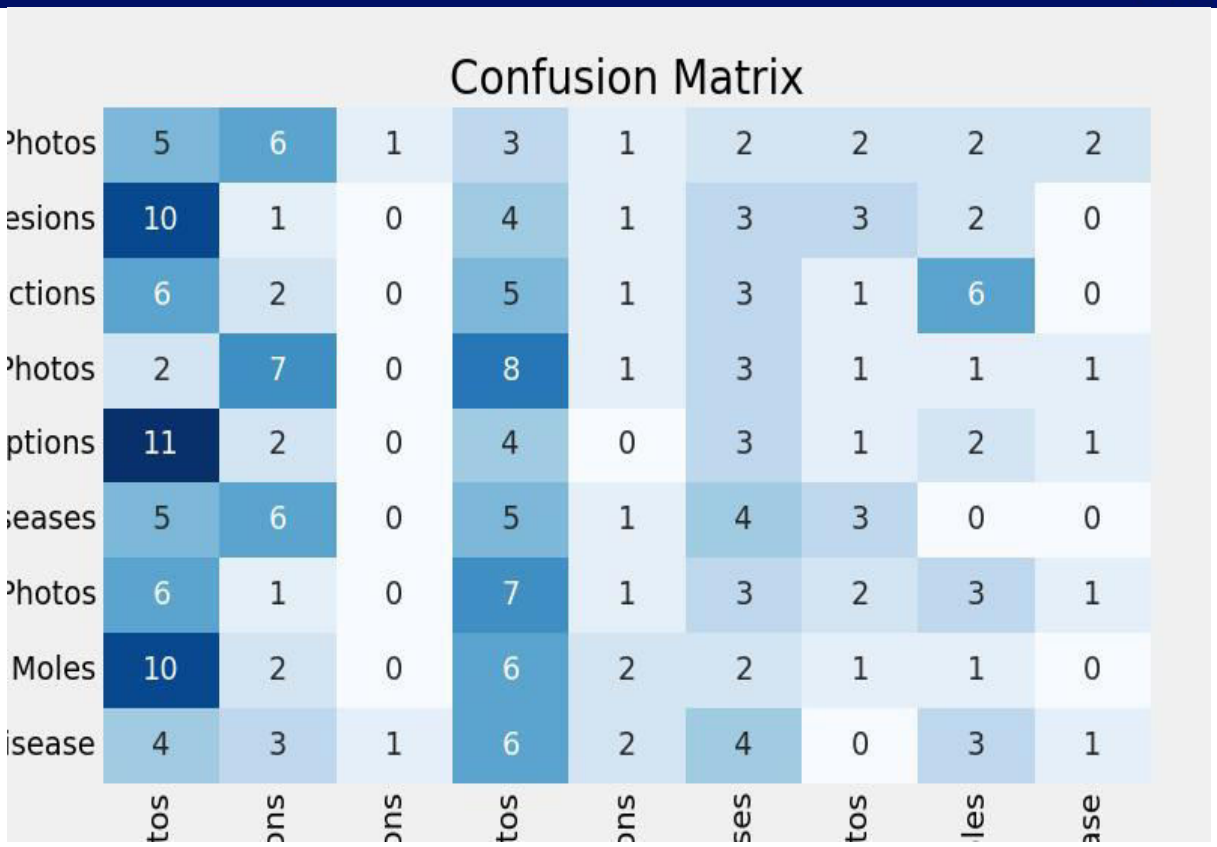

FIGURE 8. Confusion Matrix

FIGURE 9. Classification Report

Classification Report:

	precision	recall	f1-score	support
Acne and Rosacea Photos	0.0847	0.2083	0.1205	24
Actinic Keratosis Basal Cell Carcinoma and other Malignant Lesions	0.0333	0.0417	0.0370	24
Cellulitis Impetigo and other Bacterial Infections	0.0000	0.0000	0.0000	24
Eczema Photos	0.1667	0.3333	0.2222	24
Exanthems and Drug Eruptions	0.0000	0.0000	0.0000	24
Hair Loss Photos Alopecia and other Hair Diseases	0.1481	0.1667	0.1569	24
Herpes HPV and other STDs Photos	0.1429	0.0833	0.1053	24
Melanoma Skin Cancer Nevi and Moles	0.0500	0.0417	0.0455	24
Nail Fungus and other Nail Disease	0.1667	0.0417	0.0667	24
accuracy			0.1019	216
macro avg	0.0880	0.1019	0.0838	216
weighted avg	0.0880	0.1019	0.0838	216

Prediction Results:

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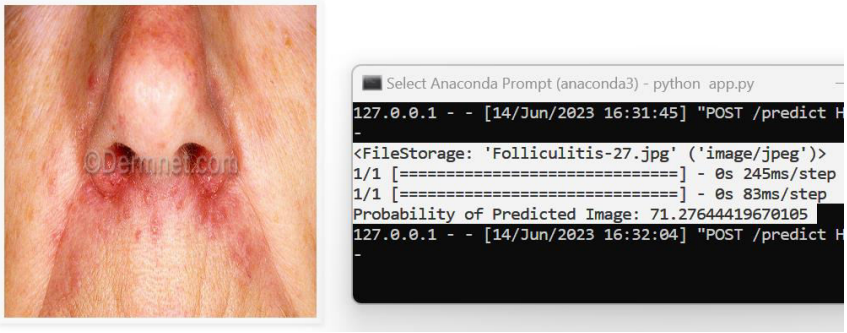

FIGURE 10. Predicted Output: Cellulitis Impetigo and Other Bacterial Infections with Probability of 71.3%

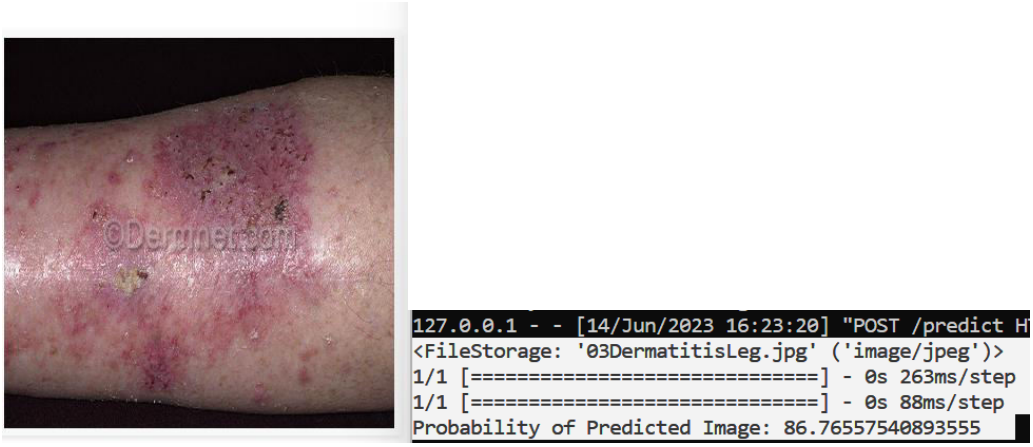

FIGURE 11. Predicted Output: Eczema Photos with Probability of 86.7%

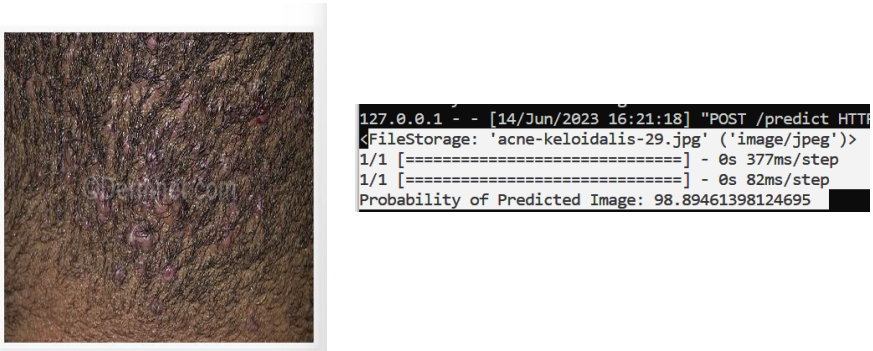

FIGURE 12. Predicted Output: Hair Loss Photos Alopecia and other Hair Diseases with Probability of 98.9%

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FIGURE 13. Predicted Output: Acne and Rosacea Photos with Probability of 94.6%

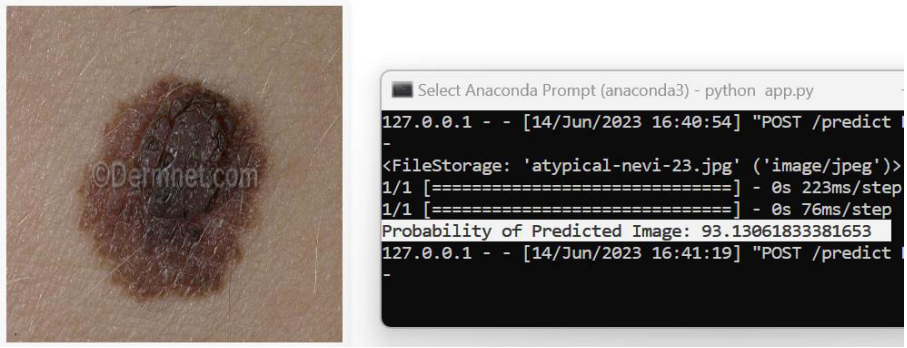

FIGURE 14. Predicted Output: Melanoma Skin Cancer Nevi and Moles with Probability of 93.1%

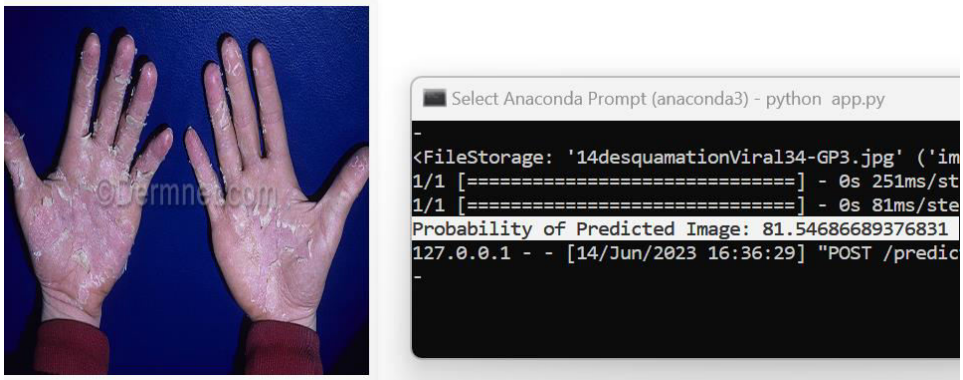

FIGURE 15. Predicted Output: Exanthems and Drug Eruptions with Probability of 81.5%

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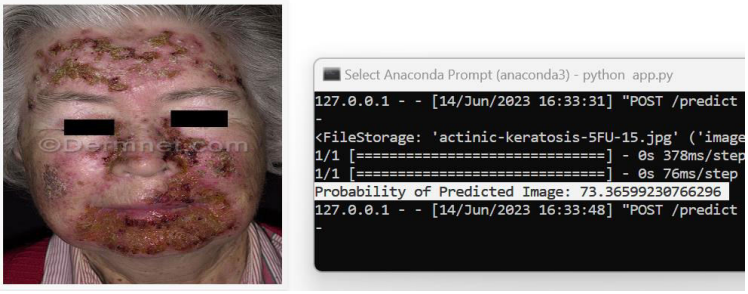

FIGURE 16. Predicted Output: Actinic Keratosis Basal Cell Carcinoma and other Malignant Lesions with Probability of 73.4%

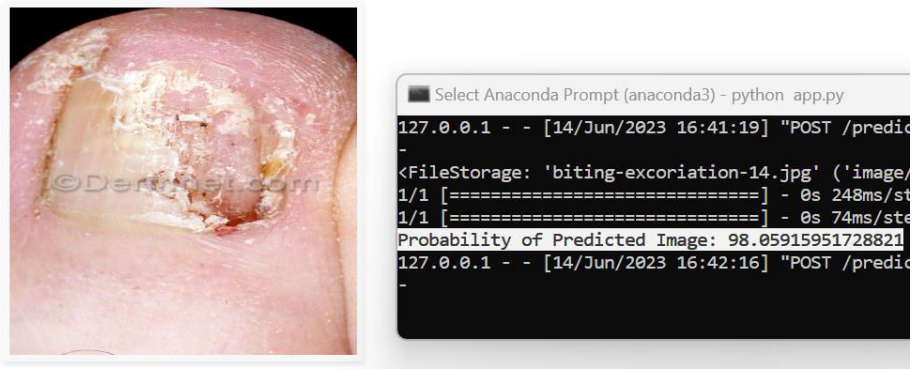

FIGURE 17. Predicted Output: Nail Fungus and other Nail Diseases with Probability of 98.05%

Class	SD-HZ			SD-HZ-C
	Train	Val	Test (Clean)	Test (Corrupted)
Acne	764	109	219	219X75 Corruptions
HZ	289	41	82	82X75 Corruptions
Tinea	555	79	159	159X75 Corruptions
Other Disease	4252	607	1215	1215X75 Corruptions
Total	5860	836	1676	1676X75 Corruptions

Table 3. Sample distribution for Training, Validation and Test

CONCLUSION

The primary goal of this research was to create a reliable and accurate DNN for mobile applications to use in identifying Herpes zoster (HZ) from other skin disorders. To do this, we created two datasets: one with 413 individual photos and 8,345 clinical images (the SD-HZ dataset) and another with 15 distinct forms of visual corruptions ranging in severity (the SD-HZ-C dataset). The latter dataset was created to test how well models fared when presented with visual corruption in their input.

On the SD-HZ dataset, thirteen DNNs were trained and then tested with both clean and corrupted images. The results showed that when choosing a model for mobile skin disease diagnostics, accuracy alone is not enough to guarantee success. MobileNet-V3-small was the model that showed the best compromise between speed and precision, making it an excellent option for real-world mobile programs.

We presented a new method called Knowledge Distillation from Ensemble through Curriculum Training (KDE-CT) to make DNNs more resistant to visual corruptions while still providing adequate performance on clean images. This strategy required periodically rearranging the training's cadre of instructors. Our results showed that KDE-CT significantly increased corruption robustness, with the student model outperforming those trained with other KDE approaches in terms of accuracy and mean corruption error (mCE). This discovery has important practical implications since it illustrates the feasibility of training a high-accuracy and -stability DNN for skin disease diagnosis from clinical photos in mobile dermatology under user-level mobile conditions.

It's worth noting that KDE-CT requires some manual tuning of hyperparameters before it can be used with a given model and data collection. Future work will focus on expanding the KDE framework to include more generic instructor selection methods, expanding the system's usefulness and adaptability.

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