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Original Article

Leprosy Skin Lesion Detection: An AI Approach Using Few Shot Learning in a Small Clinical Dataset

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This is an exploratory research study to check if artificial intelligence (AI) based image marker tool can aid leprosy screening to detect leprosy cases early in field situation and reduce the financial and personnel burden. We aimed to collect clinical leprosy skin lesion images and develop an AI model to identify and differentiate them. A total of 368 clinically diagnosed leprosy and 28 non-leprosy skin lesions were collected by an expert leprologist from 151 eligible patients using a multimodal imaging protocol. A Siamese-based Few Shot Learning (FSL) model was trained as it is a meta learning approach on an extremely small data set with fewer disease classes (disease conditions as categories). The number of class labels were increased by fine-grained grouping of skin lesions based on skin morphology (Nine leprosy subgroups) and further divided into train-set and test-set. An AI model was successfully developed, and the results indicated an accuracy of 91.25% and 73.12% on train-set and test-set for two-way one-shot task, respectively. The best sensitivity-specificity for the test-set were 72.39%-73.66% (two-way one-shot task). This early research data indicates that the development of AI based leprosy screening application is feasible using the skin lesion image as marker. The FSL method was successfully used in this training the small data set. However, this is a small sample size study, and more leprosy cases need to be enrolled along with an equal number of non-leprosy cases while improving model architecture to reduce overfit or bias problem. Moreover, as of now this tool cannot be used for neural leprosy (having no skin lesion) as well as lepromatous leprosy having diffuse infiltration. This tool will need further development and validation on pictures taken by different categories of common health care workers using available mobile phones.

Keywords : Applied Artificial Intelligence, AI, Few Shot Learning, Leprosy Screening, Siamese Network, Skin Imaging

Introduction

Despite the preventive measures to control the transmission of leprosy, 140,594 new cases were reported globally with a detection rate of 17.83 per million population during 2021. In the same year, >9000 new cases in children aged ≤15 years were reported across the world (WHO Global leprosy update, 2021). India contributed to 58%

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of global leprosy burden and the prevalence rates of pediatric leprosy ranged from 4% to 34% across the country (Narang & Kumar 2019, NLEP 2021). In India, from a total of ~135,485 new cases of leprosy, 8.7% were among children. These numbers reveal that a sizeable proportion of the newly detected cases occur in children. Among children, the disease tends to occur with the highest frequency in 5–14 years of age group and up to 6% cases are reported in children <5 years of age (Narang & Kumar 2019, Barreto et al 2014). The optimal way to prevent transmission of the disease and reduce disabilities is through early detection of leprosy followed by initiation of multidrug therapy (MDT) (Franco-Paredes & Rodriguez-Morales 2016).

According to World Health Organization (WHO), the diagnosis of leprosy for a patient not receiving MDT is validated by the presence of any one of the three cardinal signs: 1) definite loss of sensation in a pale (hypopigmented or reddish) skin patch, 2) thickened or enlarged peripheral nerve, with loss of sensation and/or weakness of the muscles supplied by that nerve, and 3) presence of acid-fast bacilli in a slit-skin smear (WHO 2012, Britton & Lockwood 2004). Diagnosis of leprosy using the slit-skin smear test requires technical expertise in taking the smear, fixation, staining, and interpretation of the result (WHO 2012, Britton & Lockwood 2004, Desikan et al 2006). Additionally, slit-skin smears are positive in multibacillary (MB) leprosy, but are not effective in identifying paucibacillary (PB) and subclinical forms of leprosy (Gautam & Jaiswal 2019). Similarly, other diagnostic methods, such as enzyme-linked immunoassay (ELISA) and lateral flow assay, show low sensitivity for PB leprosy, which is often difficult to diagnose clinically compared to MB leprosy (Da Silva et al 2010, WHO 2017). Although polymerase chain reaction (PCR)-based assays using tissue specimens show higher sensitivity and specificity than ELISA and lateral flow assays, they require standardization and are difficult to perform in most primary health care settings located in remote endemic regions (Martinez et al 2011). In addition, there are no commercially available PCR tests for leprosy diagnostics (WHO 2017).

Community-based active case detection and prompt treatment, is considered an effective strategy to eradicate leprosy (Thangaraju et al 2018); however, the active case detection in the national programs are often impacted by limited resources and other diseases taking priority over leprosy at a given time.

Compared to an expert dermatologist, it is difficult for a public health worker deployed on a leprosy screening program to identify the early signs of leprosy and confirm its complex presentation. Low case detection in decentralized and integrated leprosy control services is attributed to the lack of specialized skills, resource scarcity, and the variable presentation of leprosy disease (Kumar & Dogra 2009). In addition, existing leprosy screening guidelines result in a significant percentage of false-positive individuals undergoing unnecessary treatment due to overdiagnosis (Hofstraat & van Brakel 2016). A follow-up study evaluating earlier detection of leprosy among asymptomatic contacts demonstrated that relatively few people with positive tests go on to develop clinical leprosy, with an overall positive predictive value (PPV) of only 4% (Penna et al 2016). Hence, there is a strong unmet need to find better ways for leprosy screening in resource-constrained settings.

One potential solution to address this unmet need is developing an artificial intelligence (AI) based leprosy screening tool. Although artificial AI techniques have demonstrated promising results on their potential role to assist physicians,

radiologists, and pathologists in better clinical decision-making (Jiang et al 2017, Hosny et al 2018, Serag et al 2019, De Souza et al 2021), there have been few studies in the field of leprosy. Therefore, this study was conducted to collect clinical leprosy skin lesion images and develop an AI model to identify and differentiate leprosy skin lesions. Here we also discuss methodologies such as multimodal imaging protocol to collect skin lesion images from leprosy and non-leprosy participants with focus on the low data training approach using Siamese based Few Shot Learning (FSL). FSL is a technique in machine learning where few samples from each labelled category/ class are exposed to model during training to measure either similarity or contrast between different labelled classes.

Materials and Methods

Image collection study

Study participants

In this image collection study, leprosy skin images were captured through a non-interventional clinical study, implemented in collaboration with the Sivananda Rehabilitation Home (SRH), Hyderabad, India.

The patients were enrolled from different districts around Hyderabad in the state of Telangana, through leprosy camps organized by SRH network clinics. These leprosy camps were run in Panipura, Gadwal, Vikarabad, Karimnagar, Pitlam, and Nalgonda. Interested participants were provided with a study-specific participant information and written informed consent form. In this study we planned to enroll 500 patients with a confirmed leprosy diagnosis and with skin presentation, and another 500 patients with leprosy-like skin conditions. However, due to the global pandemic the study was stopped leading to limited skin image dataset. Hence, the study team had to develop a novel approach to utilize the limited available image data to develop an algorithm. In this study a total of 396 lesions were collected (368 leprosy and 28 non-leprosy) from 151 dermatology patients.

Patients of all ages and genders with diverse types of leprosy such as the tuberculoid, indeterminate (borderline, borderline tuberculoid, borderline lepromatous) and lepromatous leprosy were included in the study after obtaining written informed consent. For children aged <18 years, consent from the parent or legal guardian as well as the child was obtained. The patients who were treated for leprosy for more than 3 months with anti-leprosy drugs were excluded to ensure the images used for algorithm building are representative of active leprosy lesions without transformation and healing by drug therapy. The investigator applied no additional exclusions to ensure that the study population was representative of all eligible patients.

Ethical considerations

The study was initiated after obtaining approval from the Ramdev Rao Hospital's Institutional Ethics Committee (SRH is an organization under the jurisdiction of Ramdev Rao Hospital) and was conducted following the principles of the Declaration of Helsinki and the International Council for Harmonization of Technical Requirements for Pharmaceuticals for Human Use-Good Clinical Practice (ICH-GCP) guidelines.

Image collection protocol

Participants who met the eligibility criteria of the study were included by the expert leprologist (principal investigator). In majority of cases, leprosy is identified in public health screening in the later stages of the disease (borderline and lepromatous leprosy) due to lack of disease awareness. Hence, it was ascertained that the inclusion criteria should reflect the actual scenarios of leprosy public health screening. The peripheral nerves were palpated for all the patients and the information is captured in the

clinical report form (CRF) as well. However, this information is not used for the AI algorithm building. The investigator did a thorough clinical examination through inspection and palpation of lesions and captured the lesion morphology and palpation characteristics on a CRF along with the clinical history. The diagnosis of leprosy was made based on WHO criteria (WHO Expert Committee on leprosy: 8th Report 2012) and clinical spectral presentation of advanced leprosy, while the investigator selected and marked each lesion to be imaged on the CRF, with anatomical and dermatomal identifiers. The investigator also recorded the patient's sociodemographic data on the CRF, along with age and sex; no other personally identifiable data was captured. After the investigator had marked the eligible lesions to be captured, a professional photographer took the images of each lesion in different modes based on the CRF lesion markings.

Clinical and lesion meta-data

The investigator recorded the clinical history, including disease onset and duration, symptoms of loss of sensation, pruritus, pain, and signs of disease, on the CRF. In addition, the investigator identified the potential lesions for image acquisition and marked the location on the human dermatomal outline in the CRF form (Fig.1). The investigator also recorded visual inspection and palpation characteristics at each lesion level (Table 1) as morphological meta data in the CRF form.

Image capturing and imaging modes

A professional photographer captured images of the leprosy skin lesions under ambient light. For cases where the ambient light was insufficient, a 5700K LED light source was used, which mimicked ambient light. Each lesion was captured in four different modes using three imaging devices. The

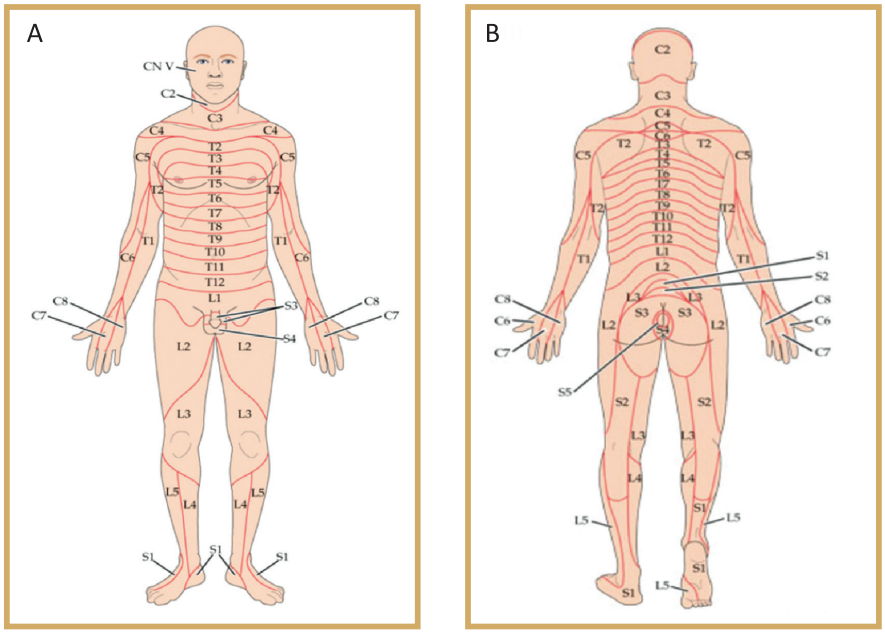

Fig. 1 : Body map for location of lesions for image capture

modes were 1) a high-resolution image captured using either Canon EOS7D or EOS 5D with an 18-135 mm STM lens; 2) a pair of high-resolution images captured using either Canon EOS7D or EOS 5D with a 100 mm Tamoran lens with a polarizing filter at two mutually perpendicular directions for each image; and 3) a mobile phone image at the highest resolution using either a Samsung S10 or iPhone X. The resolutions of SLR camera images were 5472*3648 pixels and 4900*6800 pixels and the image file formats were "RAW" and "JPEG. The images captured with Samsung mobile were in JPEG format at 3024*4032 pixels and with iPhone, the images were in HIEC format at 4032*3024 pixels. Based on either size or other characteristics, few lesions

Table 1 : List of metadata variables (clinical and lesion level)

Clinical level meta data	
Image file name	
Age	
Sex	□ Male, □ Female, □ Others
Employment status	□ Employed, □ Unemployed, □ Housewife/husband
Nature or type of employment	□ Agriculture, □ Daily wage, □ Others:__
Nutritional status	□ Undernourished, □ Normal, □ Obese
Level of undernutrition	□ Mild, □ Moderate, □ Severe
Family history of leprosy	□ Siblings, □Parents, □ Others:___, □ None
Onset of disease (First lesion appearance)	□ Onset: ___, □ Location:___
Duration of present symptoms	
Degree of skin tanning	□ None, □ Mild, □ Moderate, □ Severe
Total number of lesions	□ <2, □ 2–10, □ >10
Lesion distribution	□ Asymmetric, □ Symmetric
On leprosy medication	□ Yes, □ No
Duration of leprosy medication	
Diagnosis or leprosy	□ Tuberculoid, □ Borderline, □ Lepromatous
Diagnosis or others	
Lesion level meta data	
Anatomical location	
Dermatome	
Pigmentation	□ Hypopigmented, □ Normal pigmented, □ Hyperpigmented
Primary type	□ Macule, □ Patch, □ Plaque, □ Papule, □ Nodular
Secondary type	□ Erythema, □ Scaling, □ Lichenification, □ Excoriation, □ Ulcer
Lesion morphology	□ No demarcation, □ Demarcation, □ Elevated, □ Loss of sweat glands, □ Loss of hair follicles
Sensory examination	□ Hypesthesia, □ Anesthesia, □ Paresthesia

were captured at different fields of vision (FOV) in any one of the modes independent of other modes, adding an extra sample of the same lesion in that mode. In total, all 396 lesions were captured in four modes each and few lesions with extra samples, constituting 1931 images.

Data storage, labeling and meta-data creation

All the images captured were transferred from camera memory cards and phones to a computer and these images were identified using a naming convention as described in the study protocol to ensure the images are anonymized. Clinical history and lesion meta-data for all the patients were created in a comma-separated file (.csv), under headers described in Table 1, by a scientific research assistant who manually transcribed the CRF forms for this study. The renamed images, along with meta data in the .csv file of each of the patients, were saved on a phone memory card, a hard drive, and then transferred and saved to secure Cloud storage in all the available file formats.

Data and AI modelling

Data imbalance mitigation through image clustering to subgroups

The skin images collected in this study (few examples cited in Fig. 2) are from nine disease categories; 368 were leprosy lesions and 28 were non-leprosy lesions from the eight leprosy-like (leprosy simulants) conditions. 368 leprosy lesions include lesions with no visible pigmental change but only sensory loss, nodular lesions, infiltrative leprosy lesions and hyper-pigmented lesions other than hypopigmented, anesthetic

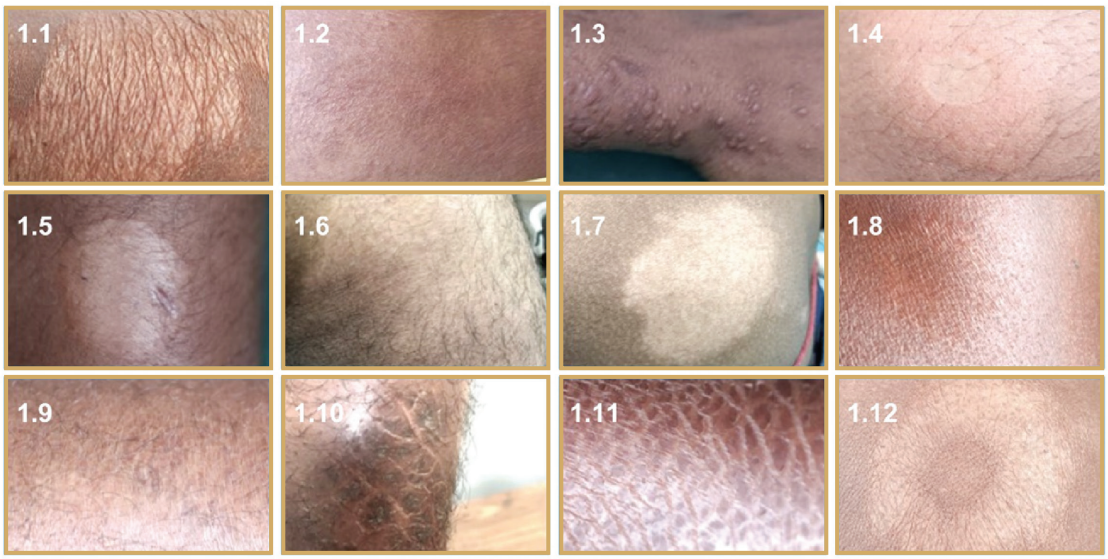

Fig 2 : Variations in the leprosy lesions: Morphology and clinical presentation

Source: The images are from the current study. 1.1 Patch, Hypopigmented, xerotic; 1.2 Patch, hypopigmented and healing; 1.3 Nodular lesion; 1.4 Patch, erythema, central healing; 1.5 Macule, hypopigmented, skin appendage loss; 1.6 Patch, hypopigmented, scaly; 1.7 Patch, hypopigmented; 1.8 Macule, red; 1.9 Patch, xerosis, normal pigmentation; 1.10 Patch, hyperpigmentation, Ichthyosis; 1.11 Patch, hyperpigmentation, Ichthyosis; 1.12 Papule, hypopigmentation, central healing

and hypoesthetic lesions. Few lesion categories with less than two lesions were excluded from clustering and from the AI model development. Since these data were extremely skewed towards leprosy and have minimal data from non-leprosy (leprosy simulant) conditions, this posed an intractable and ill-defined problem for AI training and testing. To overcome this challenge, we sub grouped each disease label into fine-grained categories based on lesion morphology and treated each sub grouped category as independent classes during training and testing (Fig. 3). Leprosy subgroup classes were labelled by adding 0 to 8 class labels to leprosy (example: leprosy_0, Leprosy_4). Train-set included leprosy 0–2, 4, 6, 8, allergic dermatitis, tinea cruris, vitiligo while, test-set had leprosy 3, 5, 7, birth mark, exfoliate dermatitis, non-leprosy, psoriasis subgroups. Subgrouping allowed a greater number of fine-grained classes and reduced skewness with long-tailed distribution, as shown in Fig. 3, which is an ideal problem that can be solved through few-shot-based meta-learning approaches. Leprosy is presented differently in terms of lesion morphology within each pathological type, such as tuberculoid, borderline, and lepromatous (WHO Leprosy factsheet 2021) (Fig. 3). Diagnosing leprosy requires the skill to identify each of these diverse presentations of the disease and translating that to an AI problem requires a similar performance from the AI model to identify each of these diverse presentations, as shown in Fig. 4.

The primary lesion type characteristics such as macule and plaques, pigmentation features such as hypo, hyper, normochromic, and other colors; along with secondary lesion characteristics including erythema, scaling, ecchymosis, healing, and scarring were used for subgrouping the 396 lesions. All these

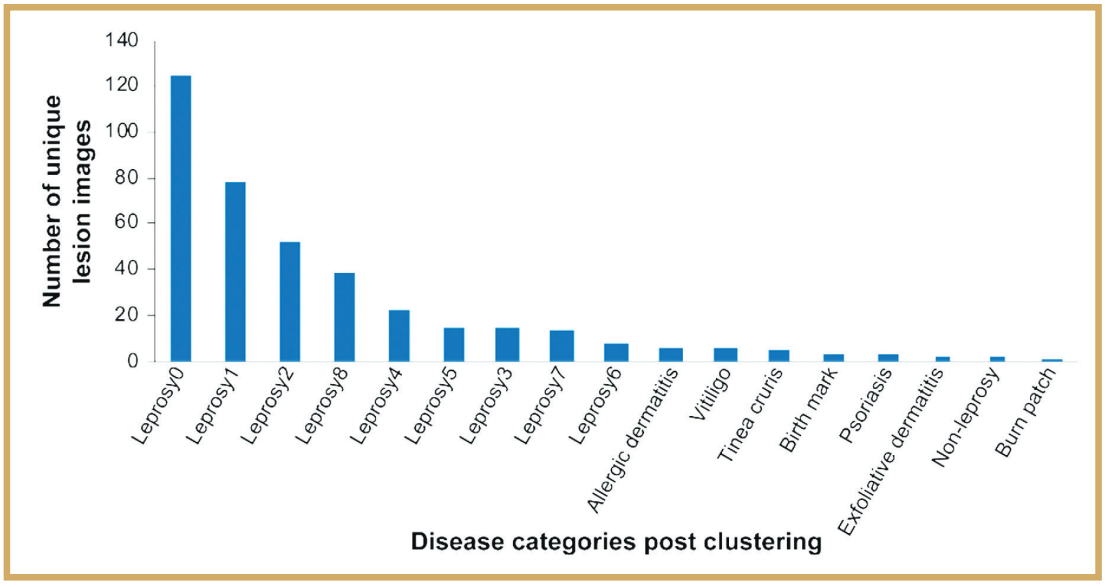

Fig. 3 : Lesion distribution after clustering following large tail pattern

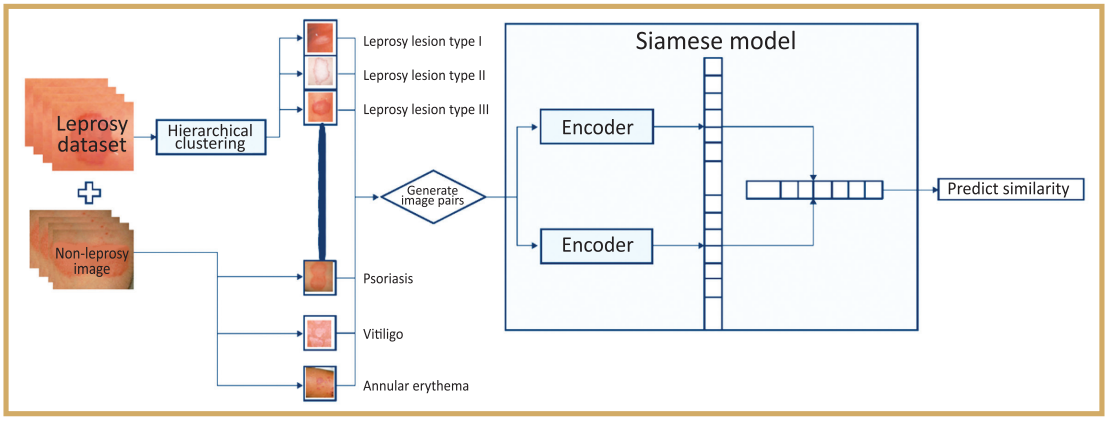

Fig. 4 : Illustration of AI study-based model architecture for leprosy identification

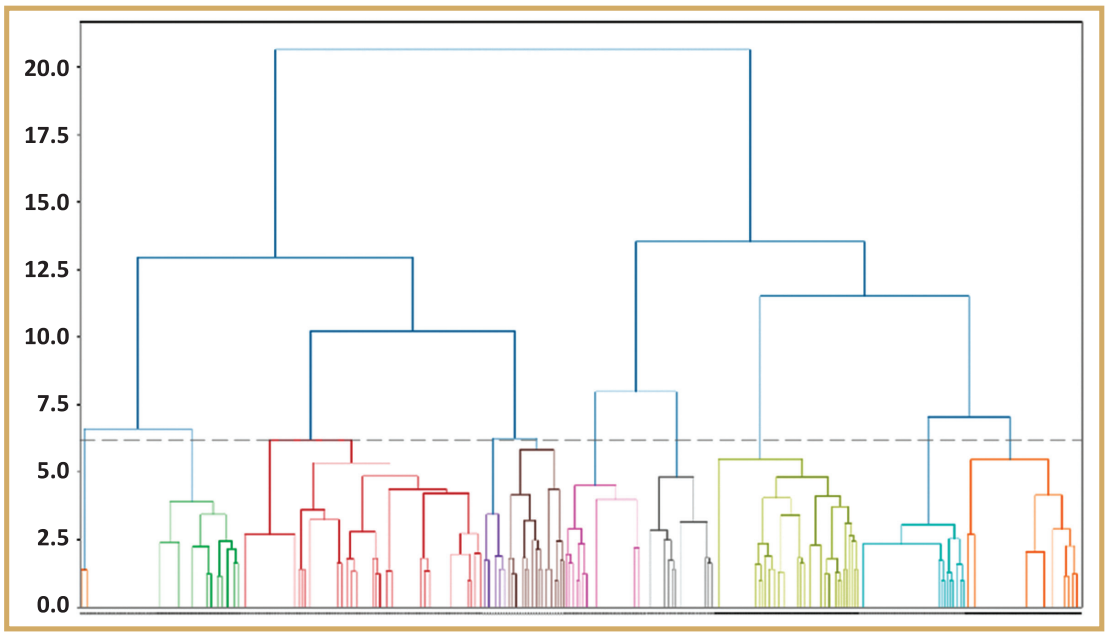

Fig. 5 : Hierarchical clustering of leprosy skin lesions (lesion morphology without skin appendages)

categorical features were converted to one-shot representations in the Python environment. A hierarchical agglomerative clustering algorithm was applied to all leprosy lesions using Ward's distance metric. At a different ward distance, we observed different number of cluster groups in

dendrogram (Fig. 5) and by choosing 9 cluster centroids, there was a better homogeneity in lesion morphology in each cluster. The remaining eight non-leprosy conditions have uniform lesion features and hence each one has only one fine-grained cluster. After excluding "burn patch," the renamed 16 categories were used for training and testing the final model.

AI model

We applied a few-shot learning-based approach using the Siamese network on this long-tailed data. The Siamese network encoder used in the study has four convolutional blocks and a flattened layer followed by a fully connected layer of 4096 dimensions. Each convolutional block has one Conv2D layer, batch normalization layer, rectified linear activation function (ReLU) layer, and a 2X2 MaxPooling2D layer with 64 filters in each block and 3*3 kernel sizes in each block. Encoder output from left and right images are fed to a lambda L2 norm layer and a final sigmoid layer. The model is trained on both binary cross-entropy loss and contrastive loss, and the results of contrastive loss-based training will be presented in this article.

Contrastive loss = $yd^2 + (1\text{-}y) \max(\text{margin} - d, 0)^2$

Experiments

The data were split into training data and test data by forming a disjoint set of train-set labels and test-set labels. Unlike the ideal data split for FSL where the train-set has data-rich classes and the test-set has data-starved classes, a few handpicked classes for testing from data-rich classes (leprosy subgroups) were integrated into the test-set, and a few tail classes were moved to the train-set, which in this case were all leprosy simulant classes (Table 2).

One of the classes was labeled as non-leprosy as the precise diagnosis requires further investigation, although leprosy was clearly excluded. Since the data were extremely small, both the train-set and test-set were used during

Table 2 : Leprosy subgroups included in training and test data classes

Classes	Leprosy subgroups
Train-set classes	Leprosy 0, Leprosy 1, Leprosy 2, Leprosy 4, Leprosy 6, Leprosy 8, Allergic dermatitis, Tinea cruris, Vitiligo
Test-set classes	Leprosy 3, Leprosy 5, Leprosy 7, Birth mark, Exfoliate dermatitis, Non-leprosy, Psoriasis

Table 3 : Accuracy results for train and test set in different models

Models	Two-way one-shot task		Three-way one-shot task	
	Train-set	Test-set	Train-set	Test-set
Siamese networks	91.25%	73.13%	89.38%	73.75%
Baseline 1 (Nearest neighbor)	40.63%	26.56%	25.63%	13.75%
Baseline 2 (Inception V3-based encoder)	37.19%	17.19%	25.31%	20.31%

Table 4 : Sensitivity and specificity results for test set in different models

Models	Two-way one-shot task		Three-way one-shot task	
	Sensitivity	Specificity	Sensitivity	Specificity
Siamese model	72.39%	73.66%	69.33%	77.65%
Baseline 2 (Inception V3-encoder)	16.42%	17.74%	12.00%	15.29%

validation runs. For Siamese-based FSL, training takes place on a batch of similar and dissimilar labeled pairs and testing happens in the n-way k-shot task. Here n is the number of classes and k is the number of examples per class.

Hyperparameters

The results presented in this paper were trained using ADAM optimizer at learning rate = 0.00005 for 40000 iterations in total. Both the training set and the testing set were validated for every 256 iterations with 160 two-way one-shot learning tasks. A batch size of 16 was used by staking two mini batches of eight at each iteration because of the limited availability of classes for training. Different batch sizes and optimizers with different hyperparameters were used however, the discussion is restricted to the results of the above experiment.

Baseline comparison model

Two models were used for baseline comparison at two different few-shot learning tasks. The first baseline is a nearest neighbor estimation based on L2-norm on images, and the second baseline is a nearest neighbor estimation based on L2-norm on pretrained inception V3 model-based embeddings.

Results

The AI model gave an accuracy of 89.38%–91.25% on training set and 73.0% on test-set on two different random few-shot tasks. Each few-shot experiment had 320 random episodic few-shot tasks. The model had better performance compared with both baselines and inception V3-based image embeddings with similar predictability to simple l2-norm on images (Table 3).

The results clearly demonstrated the advantage of metric-based learning over baselines. In addition, AI models have relatively lower loss of accuracy even at higher-way one-shot tasks.

Since four non-leprosy classes and three leprosy classes were included in the test-set, we chose to explore the model's ability to differentiate leprosy from non-leprosy. To perform this task, a sensitivity and specificity metric was developed with a one versus all approach to compute true positives and true negatives. The sensitivity and specificity (se-sp) results for the test-set were 72.39%-73.66% (two-way one-shot task) and 69.33%-77.65% (three-way one-shot task), respectively (Table 4). Although not presented in the article, corresponding values for the train-set were between 87% to 92% for both two-way and three-way learning tasks**.**

Discussion

Contribution of the study to leprosy screening

Leprosy prognosis can be significantly improved with early detection. Early diagnosis and treatment are instrumental not only in the prevention of disabilities and deformities, but also reduce the physical, psychosocial, and economic burden of the disease. A potential approach to achieve this goal could be by using evolving digital technologies; to develop a tool

that can help detect leprosy earlier compared to the current diagnostic methods which require the patient to visit a health care facility or undergo assessment by a trained health care worker (visual examination, a sensitivity test on the patch, or a smear test by a trained laboratory technician). The ideal tool should support skilled health care workers by being easy to adopt, without adding to their burden in terms of effort required and compromising predictive power in work resource-constrained settings.

This study utilized AI for the objective of leprosy screening from two directions, one from the data side and the other from the modeling and experimental side. The skin image collection for the study is designed to simulate real-world noise in data. In countries like India, AI tools for leprosy screening will be primarily used by field health care workers and due to the circumstances in which they perform, the imaging are not bound within a controlled environment, hence it is always better to train an AI model on data that simulates real-world scenario of noisy data. This AI imaging model is planned to be integrated into mobile handset which can be used by public health care workers (end users). The care flow pathway for an AI based screening tool is that once algorithm identifies high risk cases, clinical diagnosis is performed followed by MDT. In a recent study, an AI-based cross-platform app was developed for leprosy screening with the sensitivity and specificity of 93.97% and 87.09%, respectively to increase accessibility for health professionals, especially in remote diagnostic centers in Brazil (De Souza et al 2021).

Another aspect of data-related innovation is in the data subgrouping into fine-grained classes using lesion morphology and using them in the experiment as independent classes. This is fundamentally a novel approach to training as the skin lesion images in each cluster now have uniform morphological features, simulating an actual clinical decision-making system, which is primarily based on the visual semantics of lesions. This is clinically relevant because many skin diseases have diverse lesion morphological presentation due to the differences in pathological pathways, as in leprosy. This is comparatively a more robust approach as compared to that of prototypical clustering on derma skin lesions by Prabhu and colleagues (Prabhu et al 2019) due to its data centricity.

In this study, clinical data-based modelling was not utilized, primarily because certain associations, such as sensory loss (ascertained by the investigator as per the protocol), were present in almost all early leprosy lesions, which will then be an obvious predictor. A model built on clinical data has a high chance of low predictability due to subjective variability of clinical variables elicited by health care professionals. It is more relevant for leprosy as the clinical data would be elicited and entered in the AI model by health care workers. In this regard, pure image-based AI can eliminate skills-based dependencies and gaps.

Another contribution of this study is applying a Siamese network based FSL approach. This is a good approach for developing an AI tool for leprosy due to the limitations on data availability, both for leprosy and leprosy-simulant conditions commonly considered as a differential diagnosis for leprosy. Unlike the approach by Lui and colleagues where multiple skin lesion images are required (Liu et al 2020); this approach helps to train on low data while achieving satisfactory performance. A major advantage with this approach is that this model can differentiate an unseen class or disease from other classes/ conditions. This is especially useful because it is a common challenge in real screening scenarios. Other benefits include its ability to be trained

easily in new classification tasks in other skin disease domains with small datasets and that it can work in scenarios where there are several classes, which is true for leprosy due to greater number of conditions for differential diagnosis. In these conditions, traditional supervisory methods may not be efficient due to their dependency on large data for each class.

The findings of this study must be seen considering few limitations. Although the Siamese network approach is successful in FSL tasks such as face recognition and character recognition, its applicability in skin imaging requires model architecture innovation because of the FOV variations in skin imaging. A meta-learning-based approach using other related datasets can significantly improve model accuracy when combined with encoder design and hyperparameter tuning. Improving subgroup clustering by reducing noise in annotation of lesion morphology features will refine model learning. Another major limitation in our study is the lack of sufficient leprosy-simulant classes, which, if addressed, could significantly improve the model's accuracy. Though clinical data like sensory loss was not utilized for this model, adding it to image prediction scores generated from this model might help improve PPV in public health screening. This needs to be studied in a separate validation analysis. Another limitation is that the model was trained data that is labelled based on clinical diagnosis which might contribute to noisy data due to less sensitivity and specificity of clinical diagnostic criterion. To mitigate this problem and improve model learning, the model needs fine-tuning and validation on image data which is labelled based on both clinical diagnosis and laboratory confirmation. We also acknowledge that we have used WHO criterion to annotate the images and train the algorithm which may lead to potential bias in algorithm in case the data is from patients who might have incorrectly been diagnosed with leprosy. However, it must also be noted that the present study is exploratory research to check the feasibility of AI in screening and diagnosis.

In conclusion, the current study suggests that an AI based tool for extracting image-based biomarker for aiding leprosy screening is feasible. Using a small dataset of leprosy and leprosy-simulant skin images, the proposed FSL modeling approach was able to give an accuracy of 91.25% on trainset and 73.12 % on test-set. Our approach, further need supervised training on classification task with large data of leprosy and non-leprosy (leprosy simulants) which then will be validated in a clinical study to measure its effectiveness as a screening aid or tool compared with existing standards. The users will be able to use this tool after regulatory approvals post clinical validation.

The other limitations of the study are that sufficient sample size of non-leprosy skin lesions could not be included due to the Covid pandemic. In addition, this tool may not be applicable to the pure neuritic cases as well as lepromatous leprosy cases where there is no skin lesion involvement. Further development and validation of this tool needs to consider pictures taken by different categories of common health workers using available mobile phones for realizing its actual usefulness in respective health care systems.

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