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RESEARCH ARTICLE

Objective hand eczema severity assessment with automated lesion anatomical stratification

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Abstract

Hand eczema (HE) is one of the most frequent dermatoses, known to be both relapsing and remitting. Regular and precise evaluation of the disease severity is key for treatment management. Current scoring systems such as the hand eczema severity index (HECSI) suffer from intra- and inter-observer variance. We propose an automated system based on deep learning models (DLM) to quantify HE lesions' surface and determine their anatomical stratification. In this retrospective study, a team of 11 experienced dermatologists annotated eczema lesions in 312 HE pictures, and a medical student created anatomical maps of 215 hands pictures based on 37 anatomical subregions. Each data set was split into training and test pictures and used to train and evaluate two DLMs, one for anatomical mapping, the other for HE lesions segmentation. On the respective test sets, the anatomy DLM achieved average precision and sensitivity of 83% (95% confidence interval [CI] 80–85) and 85% (CI 82–88), while the HE DLM achieved precision and sensitivity of 75% (CI 64–82) and 69% (CI 55–81). The intraclass correlation of the predicted HE surface with dermatologists' estimated surface was 0.94 (CI 0.90–0.96). The proposed method automatically predicts the anatomical stratification of HE lesions' surface and can serve as support to evaluate hand eczema severity, improving reliability, precision and efficiency over manual assessment. Furthermore, the anatomical DLM is not limited to HE and can be applied to any other skin disease occurring on the hands such as lentigo or psoriasis.

KEYWORDS
anatomy, computer-assisted, diagnosis, deep learning, eczema, severity of illness index

1 | INTRODUCTION

Hand eczema (HE), also called hand dermatitis, is an inflammatory disease, often chronic, causing a wide spectrum of symptoms including redness (erythema), scaling, hyperkeratosis, fissures, vesicles and erosions.[1] All these features are visible on digital pictures. It is one of the most frequent dermatoses with 15% life prevalence and 10% 1-year prevalence in the general population. It has a multifactorial aetiology including both environmental and genetic factors.[2] HE severity range spans from mild to severe cases, the latter causing adverse physical and psychological effects, both in private and professional activities, and significant impairment to patients' quality

of life.[3,4] Globally, HE induced socio-economic burden on society is considerable.[5]

Hand eczema is a remitting and relapsing disease that can acutely flare but also persist in a chronic form. The majority of cases are characterized as occupational, and although current treatments may improve patient's conditions, the disease remains very often chronic, oscillating between acute and subacute stages.[6,7] It is therefore critical that clinicians can monitor its evolution precisely and efficiently to adapt treatment in consequence. A review reported the use of 45 different grading systems in HE research studies.[8] While all of them were based on a selection of morphological patterns and physiological abnormalities, the most accurate in terms of lesion distribution analysed the subregions of each hand separately. One of the most established systems is the hand eczema severity index (HECSI),[9] which consists in combining the rankings of six clinical signs (erythema, induration/papulation, vesicles, fissures, scaling and oedema) with the estimated surface of eczema lesions on five hand subregions (fingertips, fingers without tips, palm of hands, back of hands and wrist). The large variety of clinical signs is caused by the existence of many subtypes of the condition such as dry fissured HE, pulpitis HE, nummular HE, vesicular HE and hyperkeratotic palmar HE.[1]

In clinical practice, severity grading is not performed systematically as it is a time-consuming process (especially when grading is not performed on a regular basis) requiring both training and experience. An overall acute or chronic, mild, moderate to severe grading, eventually with photo documentation, is preferred instead. In situations where precise assessment is required such as the evaluation for fitness to work or reimbursement for expensive drugs, more objective methods like the HECSI score should be performed. Such assessments and the monitoring of disease evolution can only be performed on patients' follow-up (in-person) visits by trained clinicians. Furthermore, precision remains bounded by the discrete nature of the rankings, which induce inevitable inter- and intra-observer variations.[9] This issue was recently illustrated by two independent studies, which reported remarkably different minimal important change values for the HECSI score (41 points[10] vs. 6.3 points[11] on a theoretical maximum of 360 points).

Machine learning algorithms have the potential to assist clinicians with HE severity assessment and monitoring, improving on the efficiency, precision and simplicity of the process. Being automated, they are reproducible and promise to reduce the problem of inter- and intra-observer variations. The best results for machine vision are currently achieved with deep learning models[12,13] (DLM). In this study, we trained two separate DLMs to automatically segment HE lesions and generate the anatomical maps of patients' hands pictures. By combining these predictions, we could generate the anatomical repartition of HE lesions, which can assist with patient documentation and support the determination of severity gradings such as HECSI score.

2 | METHODS

All hand pictures were obtained at the university hospital of Zurich from adult patients, skin type 1 to type 3 on the Fitzpatrick scale over a period of 4 years starting in 2014. The hospital's dermatologists diagnosed patients with HE lesions and then sent them for imaging. Pictures were captured within the same hospital using either a dedicated device under nurse supervision (a closed box equipped with camera where patients could fit their hands) or by the hospital photographer. In both cases, capturing conditions were standardized: both hands facing up/down, fixed background (green for the device and grey for the photographer), controlled lighting and zoom levels. An aspect that was not standardized was the portion of the wrists to be included as the imaging focus was the hands. Pictures were anonymized by the removal of all patient-identifying information.

2.1 | Hand eczema data set

The HE data set was composed of 312 high-resolution pictures (156 front and back hands pairs) annotated by a team of 11 experienced dermatologists for eczema lesions, healthy skin and background. When annotations for the same picture were available, the majority consensus was computed. The data set was randomly split into 249 pictures for training and 63 for testing, ensuring no leak of pictures from the same patient. To leverage the full pixel resolution, all pictures were divided into square patches of size 512 pixels resulting in 7755 training patches and 1937 test patches.

2.2 | Hand eczema DLM training

The HE DLM was based on the U-Net[14] architecture with a ResNet[15] backbone pretrained on ImageNet.[16] HE training patches were resized to squares of 256 pixels size and the DLM was trained for 40 epochs, with a batch size of 16, the Adam[17] optimizer and one cycle scheduling[18] for a learning rate initialized at 1 e-4. To mitigate data set imbalance, we used a combination of the dice loss[19] and the focal loss.[20] Data augmentation operations consisted in random rotations, flips, brightness, contrast, perspective and zoom changes.

2.3 | Hand anatomy data set

The anatomy data set comprised 215 high-resolution hand pictures with 99 front hands and 116 back hands. Each picture was annotated by one medical student with 37 anatomical regions presented in Figure 1, including the wrist and “non-hand” (anything else) regions. The correspondence between these anatomical regions and the HECSI regions is presented in the Table S1. The data set was randomly divided into 171 pictures for training and 44 pictures for testing performance, ensuring no leak.

2.4 | Anatomy DLM training

The architecture of the anatomy DLM was similar to the HE DLM. We used the same training conditions except that the anatomy

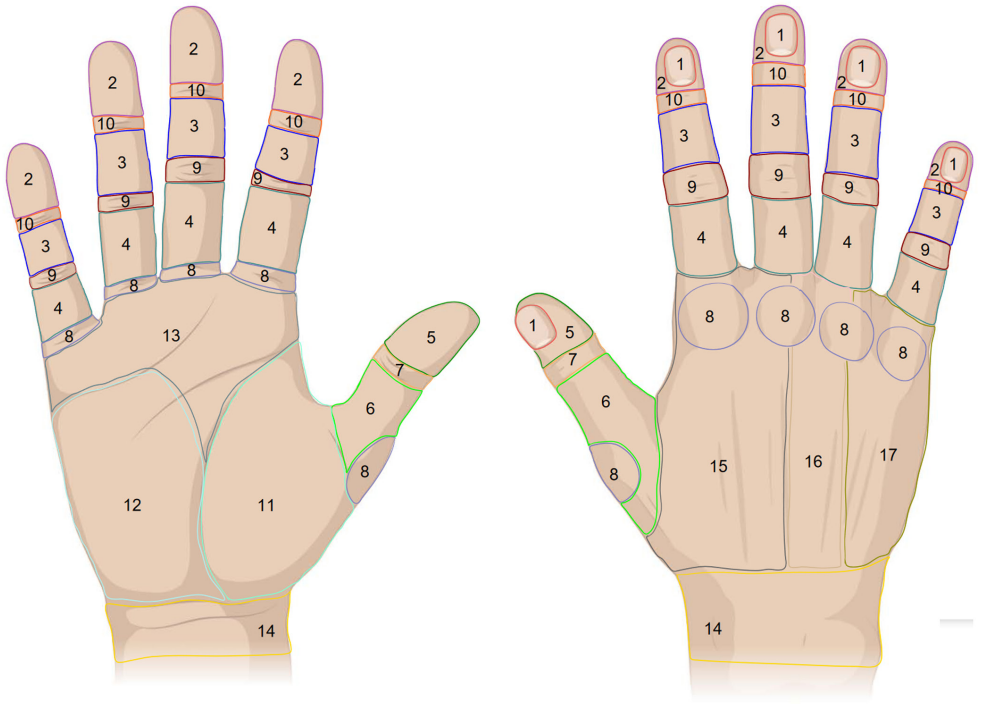

FIGURE 1 Hands' anatomical regions. his schema presents the different hands' anatomical regions used in this work: nail (1), fingers II-V distal (2), fingers II-V middle (3), fingers II-V proximal (4), thumb distal (5), thumb proximal (6), interphalangeal (IP) joint I (7), metacarpophalangeal (MCP) I-V (8), proximal IP (PIP) II-V (9), distal IP (DIP) II-V (10), thenar (11), hypothenar (12), palm (13), wrist (14), dorsal radial (15), dorsal middle (16) and dorsal lateral (17).

training pictures were resized to squares of 380 pixels side-size and that the batch size was fixed to 4.

2.5 | Hand eczema assessment workflow

The workflow of our HE severity assessment system (Figure 2) essentially consists of five steps. First, the patient's hands are photographed from both sides. Then, the HE DLM predicts the eczema lesions in the pictures, followed by the mapping of the anatomical regions by the anatomy DLM (these two steps could be executed in parallel). Finally, the predictions are merged and a disease report is generated, providing a textual description of the disease together with a quantification of eczema surface per anatomical regions.

2.6 | Analysis

The performance of the HE and anatomy DLMs were evaluated on the respective test data sets using the precision and sensitivity metrics with 95% confidence interval (CI). The CI were determined using the non-parametric bootstrap resampling method. In the case of the HE DLM, the full picture predictions were first reconstructed from the individual test patches predictions before computing the performance metrics. Furthermore, we evaluated the intraclass correlation (ICC) of the predicted HE surface with experts' annotations.

We also analysed the performance of both DLMs after aggregating their predictions over the HECSI anatomical regions. In the case of the anatomy data set, we could merge the anatomical regions labelled by the student into HECSI regions (as per Table S1), while for the HE DLM, we used the HECSI regions obtained from the anatomy DLM predictions.

To gain insights on the HE data set, we computed the average eczema surface per anatomical region with standard deviation and median. This analysis was performed based on the anatomy DLM predictions of the full HE data set and the dermatologists' HE labels.

Finally, taking an example patient case from the HE test set, we automatically generated a textual disease report with corresponding eczema anatomical stratification tables.

3 | RESULTS

3.1 | Hand eczema

The performance of the HE DLM was evaluated on the HE test set pictures (Table 1). When evaluating the performance over the full pictures, the DLM achieved a precision of 75% (CI 64–82) and a sensitivity of 69% (CI 55–81). The ICC of the predicted HE surface was 0.94 (CI 0.90–0.96) indicating a very strong correlation with experts' annotations.

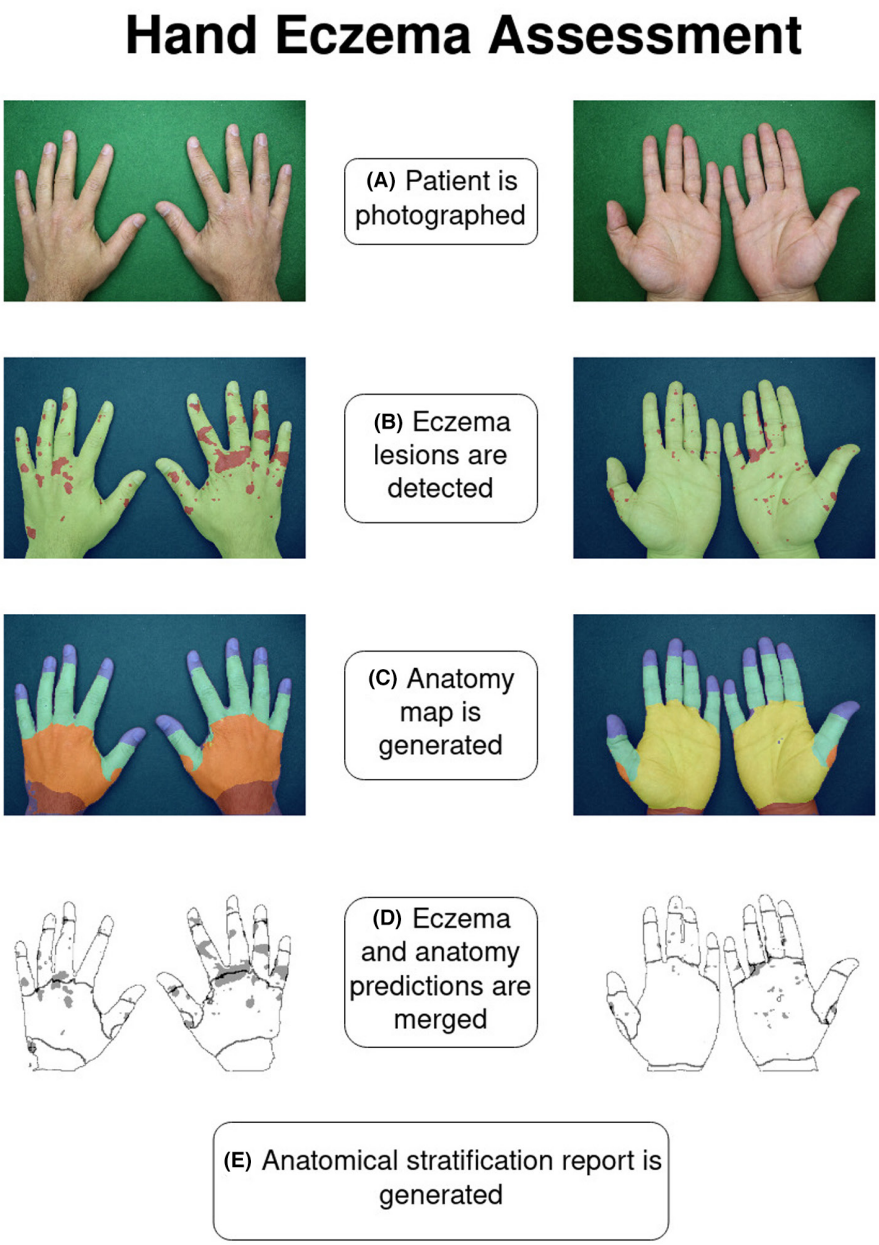

FIGURE 2 Hand eczema assessment workflow. This figure presents a patient's front and back hand pictures (A), the corresponding hand eczema deep learning model (DLM) predictions (B), the hands anatomical regions (aggregated over the same regions assessed in the hand eczema severity index system for visual clarity) mapped by the anatomy DLM (C) and the combination of both DLMs predictions (D). In (B), the background is violet, the skin is green and the eczema lesions are red. In (C), the non-hand region is violet, the wrist is red, the palm of the hand is yellow, the fingers (without tips) is light blue, the fingertips are dark blue and the back of hand is orange.

Considering the HECSI regions (predicted by the anatomy DLM) separately, we observed that the HE DLM was more precise but less sensitive on the palm of hands, fingers and fingertips similar to the average performance on full pictures. However, the opposite occurred for the wrist and back of hands, both of which tended to be covered by hairs, a known source of confusion for segmentation approaches in such settings.

The analysis of eczema anatomical stratification of the HE data set (for HECSI regions in Table 2 and for all anatomical regions in Table S2) revealed, that the regions mostly covered by eczema lesions were the fingers and fingertips with 13.1% and 12%, respectively, followed by palm of hands with 11.6%. The wrist and back of hands had the least coverage with an average of 4.7% and 5.8% and a median close to 0%. Thus, more than half of the pictures did not have any eczema lesions on these regions, which explains the relatively large confidence intervals of the predictions. For all regions, the eczema surface standard deviation was high, above 15%.

3.2 | Hand anatomy

The performance of the anatomy DLM was evaluated on the anatomy test set pictures (Table 3). In average the DLM achieved a precision of 83% (CI 80–85) and a sensitivity of 85% (CI 82–88). The limits of wrists with arms were challenging to determine due to the lack of standardization of this particular region in the training pictures. The DLM also had difficulties for some of the MPCs (especially MPC1 on the thumb) and DIPs regions, because of their small size and unclear boundaries with respect to the other anatomical regions.

For the combined experiment using both the anatomy and HE DLMs, the regions were aggregated over the HECSI regions. This

TABLE 1 Performance of the eczema deep learning model.

Regions	Category	Precision	Sensitivity
Full pictures	Background	100% (100–100)	100% (100–100)
	Skin	95% (92–98)	97% (96–98)
	Eczema	75% (64–82)	69% (55–81)
Fingertips	Eczema	74% (65–79)	70% (63–77)
Fingers (without tips)	Eczema	78% (68–84)	69% (59–79)
Palm of hand	Eczema	78% (64–86)	84% (69–90)
Back of hand	Eczema	66% (23–85)	50% (20–85)
Wrist	Eczema	68% (27–87)	44% (19–86)
Average of HECSI regions	Eczema	71% (53–80)	62% (50–78)

Note: Performance evaluated on the hand eczema test set by comparing the eczema deep learning model predictions with the dermatologists' lesion annotations. Parentheses indicate the 95% confidence interval. The hand eczema severity index (HECSI) regions were predicted by the anatomy deep learning model.

TABLE 2 Anatomical stratification of eczema lesions.

Regions	Surface average	Surface standard deviation	Surface median	Surface interquartile range
Back of hand	5.8%	17.4%	0.2%	1.9%
Fingertips	12%	19.2%	4%	13.3%
Fingers (without tips)	13.1%	21.8%	3.9%	12.8%
Palm of hand	11.6%	22.8%	1.6%	10.7%
Wrist	4.7%	16.5%	0%	0%

Note: Eczema surface repartition over the hand eczema severity index anatomical regions. Evaluated on the full hand eczema data set using dermatologists' lesion annotations and the anatomy deep learning model predictions.

yielded a high performance since the regions' separations are more clearly defined: the average precision and sensitivity were 91% (CI 90–92) and 94% (CI 93–94).

3.3 | Disease report generation

Figure 1 presents a random patient case from the HE test data set with the predicted eczema lesions and HECSI anatomical regions. Our system automatically generated the following textual description for this patient's condition: "The patient's hands show eczema lesions on both the palmar and back sides, namely on 4.8% of the fingertips, 11% of the fingers (without tips), 1.5% of the palms, 3% of the back of hands and 1.1% of the wrists".

4 | DISCUSSION

Hand eczema is a highly prevalent disease that is often chronic and requires diligent and detailed clinical follow-up. Objective disease quantification is key for judging the success of clinical management but is challenging to perform in practice, as it requires time and expertize. In this work, we present an automated method to analyse the anatomical repartition of HE lesions from patients' hands pictures. Our approach leveraged two DLMs, one to segment HE lesions with precision and sensitivity 75% (CI 64–82) and 69% (CI 55–81), the second to segment hands anatomical regions with precision and sensitivity 83% (CI 80–85) and 85% (CI 82–88). In application of our approach, we could automatically generate the quantitative and textual description of a test patient's condition as well as compute statistics on the anatomical repartition of eczema lesions in our data set.

Commenting on the reported model performance, the sensitivity of a DLM is always a trade-off with its precision. The large confidence intervals are explained by the small size of the test data set together with the observation that a large proportion of the pictures had little to no eczema in certain anatomical regions. Given additional training data, the model sensitivity and precision could theoretically be improved. It is important to consider that the perfect segmentation of eczema lesions is not the most important objective of this study but rather the robust quantification of eczema lesions in a reproducible manner to enable precise disease monitoring in time and patient follow-up.

To the best of our knowledge, this study is the first to generate a mapping of hands' anatomical regions from patients' pictures as well as the anatomical stratification of HE lesions. Other work related to hand segmentation focused either on hand detection,[21] palm region extraction for biometrics,[22] gesture recognition[23] or bone segmentation from ultrasound and MRI scans.[24,25] Previous work on automated eczema severity assessment were based on smaller data sets and mainly proposed lesion segmentation approaches,[26] some with classification of the overall severity level.[27–29] One study's approach consisted in the detection (as opposed to segmentation) of atopic eczema lesions based on 1393 patients' pictures followed by the severity classification of seven clinical signs.[30] Segmentation and classification of eczema lesions was also performed on histopathological slides.[31]

TABLE 3 Performance of the hand anatomy deep learning model.

Regions	Precision	Sensitivity
Non-hand	99% (99–99)	97% (97–98)
DIP2	71% (58–79)	82% (72–88)
DIP3	77% (72–81)	84% (74–90)
DIP4	72% (67–78)	84% (73–90)
DIP5	75% (69–80)	85% (80–90)
IP	79% (76–82)	84% (81–87)
MCP1	64% (57–71)	79% (74–84)
MCP2	74% (69–79)	82% (74–86)
MCP3	75% (69–79)	84% (79–88)
MCP4	68% (60–75)	77% (69–83)
MCP5	72% (65–77)	79% (75–84)
PIP2	84% (75–90)	88% (82–92)
PIP3	87% (84–90)	85% (72–91)
PIP4	84% (78–88)	87% (84–90)
PIP5	84% (79–87)	86% (82–89)
Dorsal mid	72% (67–77)	76% (69–81)
Dorsal radial	86% (81–89)	85% (82–88)
Dorsal ulnar	87% (85–89)	77% (69–81)
Hypothenar	87% (84–90)	89% (81–95)
Index distal	85% (78–92)	88% (82–92)
Index middle	84% (74–91)	88% (83–92)
Index proximal	87% (81–92)	89% (83–93)
Little f. distal	90% (87–93)	89% (82–93)
Little f. middle	91% (89–93)	85% (82–88)
Little f. proximal	87% (85–90)	88% (86–91)
Middle f. distal	91% (87–94)	87% (80–93)
Middle f. middle	92% (87–94)	88% (82–92)
Middle f. proximal	89% (85–92)	88% (80–92)
Nail	89% (86–91)	83% (78–86)
Palm	89% (86–93)	86% (84–89)
Ring f. distal	87% (82–92)	87% (76–93)
Ring f. middle	89% (83–94)	86% (78–91)
Ring f. proximal	88% (84–91)	88% (84–91)
Thenar	88% (83–91)	89% (85–92)
Thumb distal	92% (90–93)	89% (86–92)
Thumb proximal	87% (83–90)	80% (76–83)
Wrist	69% (64–74)	86% (83–89)
Average	83% (80–85)	85% (82–88)
HECSI regions	Precision	Sensitivity
Non-hand	99% (99–99)	97% (97–98)
Fingertips	96% (95–96)	94% (92–95)
Fingers (without tips)	94% (93–95)	94% (93–95)
Palm of hand	96% (95–97)	98% (96–98)
Back of hand	93% (90–94)	93% (92–95)
Wrist	69% (64–74)	86% (83–89)
Average	91% (90–92)	94% (93–94)

Note: Performance evaluated on the anatomy test set by comparing the anatomy deep learning model predictions with the medical student's annotations. Parentheses indicate the 95% confidence interval. HECSI stands for the hand eczema severity index, IP for interphalangeal joint I, MCP for metacarpophalangeal, PIP for proximal IP, DIP for distal IP, f for finger.

A particular challenge faced in this study concerned the boundaries of the different hand anatomical regions. These are not clearly defined in the anatomy literature and are subject to personal interpretation in practice. In this work, unclear region frontiers were clarified with a board-certified dermatologist. The difficulties of the anatomy DLM with the determination of wrists' limits on arms were caused by variations in the training set pictures of the visible portion of wrists. This aspect was not fully standardized in the collection protocol as the photographer's goal was to capture full hands.

Further clinical studies are required to robustly differentiate mild, moderate and severe HE. Our method can be used to support clinicians in this regard by providing precise quantification of the anatomical repartition of eczema surface. These estimates have the advantage to be automated and reproducible, independent from experience or training, eliminating inter- and intra-observer variance. The results can be automatically translated to disease reports and thus assist in the documentation of patients' conditions. This approach enables less experienced clinicians to produce objective and comparable evaluation of their patients. Follow-ups can be performed remotely, either by directly integrating DLMs into mobile phone apps or by serving predictions via a web server. In this case, the picture acquisition process should be guided to ensure the captured pictures are sufficiently standardized and similar to this study's data sets. When HECSI scores are to be computed, predicted surface estimates can be combined with dermatologist's manual severity grading of HE clinical signs, all of which can be achieved remotely with classic store-and-forward teledermatology.[32]

With our method, the typical anatomical stratification of eczema lesions could be evaluated from large HE databases (similarly to Table 2 and Table S2) to help determine the regions that are more prone to develop eczema lesions and to which proportions. Similarly, the clinical evolution of individual patients' HE, and the effects of treatment could be monitored with high precision and benefit drug development efforts.

The presented hand anatomy DLM is not restricted to HE and can be equivalently used to determine the anatomical repartition of other diseases affecting hands such as lentigo, psoriasis, vitiligo or palmoplantar pustulosis. Furthermore, our anatomical segmentation approach can be applied equivalently to other body regions enabling similar applications.

4.1 | Limitations

One limitation of this study was caused by the data sets' characteristics, which only comprised hands from skin type 1 to 3 on the Fitzpatrick scale photographed in a standardized position (cf. Figure 1). As a result, the DLMs presented in this study will underperform on pictures from patient with other skin types or with hands in different position, for example, closed fists. Furthermore, the DLM could mistakenly segment benign skin lesions such as seborrheic keratoses since they were not included in the training data

set. These issues can be mitigated by retraining the DLMs on more complete data sets. Another limitation by design is that our approach does not evaluate the severity of eczema clinical signs, necessary to fully automate the HECSI score. This choice was caused by the lack of necessary data (each feature is ranked on four severity levels, all of which would require corresponding pictures to train a DLM for automation) and is planned as future work together with a prospective study on how HECSI scores correlate with this study's surface predictions. Finally, picture-based approaches such as ours, must inevitably base their predictions on limited information. Thus, for applications with high precision requirements, it is of interest to explore other image modalities that provide additional information such as multispectral imaging.[33]

5 | CONCLUSION

Taken together, by quantifying aspects of patients' conditions, our approach translates information that could so far, only be inferred and interpreted by dermatologists, into an easily shareable, objective and accessible digest. The determination of condition-specific actionable rules is the next step to empower less specialized clinicians and scale-up HE care.

AUTHOR CONTRIBUTIONS

Ludovic Amruthalingam: Conceptualization, data curation, formal analysis, investigation, methodology, project administration, software, validation, visualization, writing—original draft and writing—review and editing. Nora Mang: Data curation. Philippe Gottfrois: Methodology and validation. Alvaro Gonzalez Jimenez: Methodology and validation. Julia-Tatjana Maul: Methodology, validation and writing—review and editing. Michael Kunz: Data curation, methodology and validation. Marc Pouly: Conceptualization, funding acquisition, methodology, project administration, resources, supervision, validation and writing—review and editing. Alexander A. Navarini: Conceptualization, data curation, funding acquisition, methodology, project administration, resources, supervision, validation and writing—review and editing.

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CONFLICT OF INTEREST

Maul JT has served as advisor and/or received speaking fees and/or participated in clinical trials sponsored by AbbVie, Almirall, Amgen, BMS, Celgene, Eli Lilly, LEO Pharma, Janssen-Cilag, MSD, Novartis, Pfizer, Pierre Fabre, Roche, Sanofi and UCB. Navarini AA declares being a consultant and advisor and/or receiving speaking fees and/or grants and/or served as an investigator in clinical trials for AbbVie, Almirall, Amgen, Biomed, BMS, Boehringer Ingelheim, Celgene, Eli Lilly, Galderma, GSK, LEO Pharma, Janssen-Cilag, MSD, Novartis, Pfizer, Pierre Fabre Pharma, Regeneron, Sandoz, Sanofi and UCB.

DATA AVAILABILITY STATEMENT

Under Swiss regulations, this study's ethical permission (EKNZ, 2018 - 01074) did not include sharing patients' pictures.

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REFERENCES

1. Agner T, Aalto-Korte K, Andersen KE, et al. European environmental and contact dermatitis research group. Classification of hand eczema. *J Eur Acad Dermatol Venereol*. 2015;29(12):2417-2422.
2. Agner T, Elsner P. Hand eczema: epidemiology, prognosis and prevention. *J Eur Acad Dermatol Venereol*. 2020;34:4-12.
3. Nørreslet LB, Agner T, Sørensen JA, Ebbehøj NE, Bonde JP, Fisker MH. Impact of hand eczema on quality of life: metropolitan versus non-metropolitan areas. *Contact Dermatitis*. 2018;78(5):348-354.
4. Oosterhaven JA, Ofenloch RF, Schuttelaar ML. Validation of the Dutch quality of life in hand eczema questionnaire (QOLHEQ). *British Journal of Dermatology*. 2020;183(1):86-95.
5. Politiek K, Oosterhaven JA, Vermeulen KM, Schuttelaar ML. Systematic review of cost-of-illness studies in hand eczema. *Contact Dermatitis*. 2016;75(2):67-76.
6. Apfelbacher CJ, Ofenloch RF, Weisshaar E, et al. Chronic hand eczema in Germany: 5-year follow-up data from the CARPE registry. *Contact Dermatitis*. 2019;80(1):45-53.
7. De León FJ, Berbegal L, Silvestre JF. Management of chronic hand eczema. *Actas Dermosifiliogr (English Edition)*. 2015;106(7):533-544.
8. Weistenhöfer W, Baumeister T, Drexler H, Kütting B. An overview of skin scores used for quantifying hand eczema: a critical update according to the criteria of evidence-based medicine. *Br J Dermatol*. 2010;162(2):239-250.
9. Held E, Skoet R, Johansen JD, Agner T. The hand eczema severity index (HECSI): a scoring system for clinical assessment of hand eczema. A study of inter-and intraobserver reliability. *Br J Dermatol*. 2005;152(2):302-307.
10. Oosterhaven JA, Schuttelaar ML. Responsiveness and interpretability of the hand eczema severity index. *Br J Dermatol*. 2020;182(4):932-939.
11. Yüksel YT, Agner T, Ofenloch R. New evidence on the minimal important change (MIC) for the hand eczema severity index (HECSI). *Contact Dermatitis*. 2021;85(2):164-170.
12. Yuan Y, Chen X, Chen X, Wang J. Segmentation transformer: object-contextual representations for semantic segmentation. arXiv preprint arXiv:1909.11065. 2019.
13. Wortsman M, Ilharco G, Gadre SY, et al. Model soups: averaging weights of multiple fine-tuned models improves accuracy without increasing inference time. arXiv preprint arXiv:2203.05482. 2022.
14. Ronneberger O, Fischer P, Brox T. U-net: convolutional networks for biomedical image segmentation. *International Conference on Medical Image Computing and Computer-Assisted Intervention*. Springer; 2015:234-241.
15. He K, Zhang X, Ren S, Sun J. Deep residual learning for image recognition. *Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition*. IEEE; 2016:770-778.
16. Deng J, Dong W, Socher R, Li LJ, Li K, Fei-Fei L. Imagenet: a large-scale hierarchical image database. *2009 IEEE Conference on Computer Vision and Pattern Recognition*. Ieee; 2009:248-255.
17. Kingma DP, Ba J. Adam: a method for stochastic optimization. arXiv preprint arXiv:1412.6980. 2014.
18. Smith LN. A disciplined approach to neural network hyper-parameters: part 1–learning rate, batch size, momentum, and weight decay. arXiv preprint arXiv:1803.09820. 2018 .

19. Zhu W, Huang Y, Zeng L, et al. AnatomyNet: deep learning for fast and fully automated whole-volume segmentation of head and neck anatomy. *Med Phys*. 2019;46(2):576-589.
20. Lin TY, Goyal P, Girshick R, He K, Dollár P. Focal loss for dense object detection. *Proceedings of the IEEE International Conference on Computer Vision*. IEEE; 2017:2980-2988.
21. Urooj A, Borji A. Analysis of hand segmentation in the wild. *Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition*. IEEE; 2018:4710-4719.
22. Ito K, Suzuki Y, Kawai H, et al. HandSegNet: hand segmentation using convolutional neural network for contactless palmprint recognition. *IET Biom*. 2022;11(2):109-123.
23. Paul S, Bhattacharyya A, Mollah AF, Basu S, Nasipuri M. Hand segmentation from complex background for gesture recognition. *Emerging Technology in Modelling and Graphics*. Springer; 2020:775-782.
24. Kayalibay B, Jensen G, van der Smagt P. CNN-based segmentation of medical imaging data. arXiv preprint arXiv:1701.03056. 2017.
25. Sultan MS, Martins N, Ferreira MJ, Coimbra MT. Segmentation of bones and MCP joint region of the hand from ultrasound images. *2015 37th Annual International Conference of the IEEE Engineering in Medicine and Biology Society (EMBC)*. IEEE; 2015:3001-3004.
26. Schnürle S, Pouly M, vor der Brück T, Navarini A, Koller T. On using support vector machines for the detection and quantification of hand eczema. *ICAART*. Springer; 2017:75-84.
27. Alam MN, Munia TT, Tavakolian K, Vasefi F, MacKinnon N, Fazel-Rezai R. Automatic detection and severity measurement of eczema using image processing. *2016 38th Annual International Conference of the IEEE Engineering in Medicine and Biology Society (EMBC)*. IEEE; 2016:1365-1368.
28. Nisar H, Ch'ng YK, Ho YK. Automatic segmentation and classification of eczema skin lesions using supervised learning. *2020 IEEE Conference on Open Systems (ICOS)*. IEEE; 2020:25-30.
29. Ch'ng YK, Nisar H, Yap VV, Yeap KH, Tang JJ. Segmentation and grading of eczema skin lesions. *2014 8th International Conference on Signal Processing and Communication Systems (ICSPCS)*. IEEE; 2014:1-5.
30. Pan K, Hurault G, Arulkumaran K, Williams HC, Tanaka RJ. EczemaNet: automating detection and severity assessment of atopic dermatitis. *International Workshop on Machine Learning in Medical Imaging*. Springer; 2020:220-230.
31. Scheurer J, Ferrari C, Berenguer Todo Bom L, Beer M, Kempf W, Haug L. Semantic segmentation of histopathological slides for the classification of cutaneous lymphoma and eczema. *Annual Conference on Medical Image Understanding and Analysis*. Springer; 2020:26-42.
32. Kanthraj GR. Classification and design of teledermatology practice: what dermatoses? Which technology to apply? *J Eur Acad Dermatol Venereol*. 2009;23(8):865-875.
33. Hald M, Thyssen JP, Zachariae C, et al. Multispectral imaging of hand eczema. *Contact Dermatitis*. 2019;81(6):438-445.

SUPPORTING INFORMATION

Additional supporting information can be found online in the Supporting Information section at the end of this article.

Appendix S1:

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