A deep learning system for differential diagnosis of skin diseases

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Skin conditions affect 1.9 billion people. Because of a shortage of dermatologists, most cases are seen instead by general practitioners with lower diagnostic accuracy. We present a deep learning system (DLS) to provide a differential diagnosis of skin conditions using 16,114 de-identified cases (photographs and clinical data) from a teledermatology practice serving 17 sites. The DLS distinguishes between 26 common skin conditions, representing 80% of cases seen in primary care, while also providing a secondary prediction covering 419 skin conditions. On 963 validation cases, where a rotating panel of three board-certified dermatologists defined the reference standard, the DLS was non-inferior to six other dermatologists and superior to six primary care physicians (PCPs) and six nurse practitioners (NPs) (top-1 accuracy: 0.66 DLS, 0.63 dermatologists, 0.44 PCPs and 0.40 NPs). These results highlight the potential of the DLS to assist general practitioners in diagnosing skin conditions.

Skin and subcutaneous disease is the fourth leading cause of nonfatal disease burden globally, affecting 30–70% of individuals and prevalent in all geographies and age groups. Skin disease is also one of the most common chief complaints in primary care, with 8–36% of patients presenting with at least one skin complaint. However, dermatologists are consistently in short supply, particularly in rural areas, and consultation costs are rising. Thus, the burden of triage and diagnosis commonly falls on non-specialists such as primary care physicians (PCPs), nurse practitioners (NPs) and physician assistants. Because of limited knowledge and training in a specialty with hundreds of conditions, diagnostic accuracy of non-specialists is only 24–70%. Diagnostic accuracy can be improved by using references such as dermatology textbooks, UpToDate and online image search engines. Low diagnostic accuracy can lead to poor patient outcomes such as delayed or improper treatment.

To expand access to specialists, store-and-forward teledermatology has become more popular, with a 48% increase in US non-governmental programs between 2011 and 2016. In store-and-forward teledermatology, digital images of affected skin areas, typically captured with digital cameras or smartphones, are transmitted along with other medical information to a dermatologist. The dermatologist then remotely reviews the case and provides consultation on the diagnosis, work-up, treatment and recommendations for follow-up. This approach has been shown to result in similar clinical outcomes to conventional consultation in dermatology clinics, and improved satisfaction from both patients and providers.

The use of artificial intelligence tools may be another promising method of broadening the availability of dermatology expertise. Recent advances in deep learning have facilitated the development of artificial intelligence tools to assist in diagnosing skin disorders from images. Many previous works have focused on the visual recognition of skin lesions from dermoscopic images, which requires a dermatoscope. However, dermatoscopes are usually inaccessible outside of dermatology clinics and are unnecessary for many common skin diseases. By contrast, others have considered clinical photographs for skin cancers, onychomycosis and skin lesions from an educational website. Several works have also reported comparable performance to experts on binary classification tasks (benign versus malignant) or on skin lesion conditions, dermatoses and pigmentary issues. These skin problems have yet to be addressed despite their high prevalence and similarly low diagnostic accuracy by non-specialists.

Moreover, previous works have focused on predicting a single diagnosis, instead of a full differential diagnosis. A differential diagnosis is a ranked list of diagnoses that is used to plan treatments in the common setting of diagnostic ambiguity in dermatology, and can capture a more comprehensive assessment of a clinical case than a single diagnosis.

In this article, we report a deep learning system (DLS) to identify 26 of the most common skin conditions in adult cases that were referred for teledermatology consultation. As a secondary prediction, the DLS also outputs predictions for the full set of 419 skin conditions seen in this work. Our DLS provides several advances relative to previous work. First, instead of a single classification between a small number of conditions, our DLS provides a differential diagnosis across 26 conditions, including various dermatitides, dermatoses, pigmentedary conditions, alopecia and lesions, to aid clinical decision making. Second, instead of relying only on images, the DLS leverages 45 types of data that are available to dermatologists in a teledermatology service, such as demographic information and medical history. Third, the DLS supports a variable number of input images, and the benefit of using multiple images was assessed. Finally, to understand the potential value of the DLS, we compared...
its diagnostic accuracy with that of board-certified clinicians with three different levels of training: dermatologists, PCPs and NPs.

Results

Overview of approach. Our DLS has two major components: a variable number of deep convolutional neural network modules to process a flexible number of input images, and a shallow module to process metadata such as demographic information and medical history (Fig. 1 and Supplementary Table 1). To develop and validate our DLS, we applied a temporal split to teledermatology cases: the first 80% of the cases (years 2010–2017) for development and the last 20% (years 2017–2018) for validation (Table 1 and Supplementary Fig. 1). The reference standard for each case was determined by the aggregated opinions of multiple dermatologists who reviewed the case independently (see Methods). After excluding cases with multiple skin conditions and those that were non-diagnosable, 16,114 cases (64,837 images) were used for development and 3,756 cases (14,883 images) for validation (validation set ‘A’; a smaller subset ‘B’ was used for comparison with clinicians and is described in the relevant sections). In total, 64,878 dermatologist reviews were collected for development and 11,268 reviews for validation.

DLS performance. The DLS’s top differential diagnosis in validation set A had a ‘top-1 accuracy’ (accuracy across all cases for 26 skin conditions + ‘other’) of 0.71 and a ‘top-1 sensitivity’ (sensitivity computed for the 26 conditions separately and averaged) of 0.58 (Fig. 2a and Supplementary Table 2). When the DLS was allowed three diagnoses (for example, to mimic a clinical decision support tool that suggests a few possibilities for the clinician’s consideration), the DLS’s top-3 accuracy rose to 0.93 and its top-3 sensitivity across 26 conditions rose to 0.83. To ensure that the DLS was not biased against different skin tones, we evaluated DLS accuracy stratified by estimated Fitzpatrick skin type (Table 1) and self-reported race/ethnicity (Supplementary Table 3). Among the Fitzpatrick skin types that comprised at least 2% of the data (types II–V), the top-1 accuracy ranged from 0.70 to 0.74 and the top-3 accuracy ranged from 0.91 to 0.95. Additional subanalyses based on self-reported demographic information (that is, age, sex, race, ethnicity) are presented in Supplementary Table 3. Evaluation of the DLS’s overall differential diagnosis using the average overlap (AO) metric yielded 0.68 overall (Fig. 2b) and 0.66–0.69 when stratified by Fitzpatrick skin types (types II–V, Supplementary Table 3). The DLS performance for each of the 26 conditions is presented in Extended Data Fig. 1 and the results across 419 skin conditions are presented in Extended Data Fig. 2.

DLS performance compared with clinicians. To compare the DLS performance with that of clinicians, validation set A was randomly subsampled (stratified by condition). This produced 963 cases (3,707 images; validation set B) enriched for rarer conditions (for example, 2–5% prevalence in B compared to below 1% in A). Eighteen clinicians of three different levels of training (dermatologists, PCPs and NPs, all of whom were board-certified) graded validation set B. On this smaller dataset, the DLS achieved a top-1 accuracy of 0.73, compared to 0.63 for dermatologists, 0.44 for PCPs and 0.40 for NPs (Fig. 2a). The DLS was non-inferior to the dermatologists at a 5% margin (P < 0.001). The top-3 accuracy was substantially higher at 0.90 for the DLS, compared to 0.75 for dermatologists, 0.60 for PCPs and 0.55 for NPs. Consistent with the top-1 and top-3 accuracies, evaluation of the full differential diagnosis using
| Characteristics                                               | Development set | Validation set A | Validation set B (enriched subset of ‘A’) |
|---------------------------------------------------------------|-----------------|------------------|------------------------------------------|
| Years                                                          | 2010 to 2017    | 2017 to 2018     | 2017 to 2018                             |
| Total no. of cases                                            | 16,530          | 4,146            | N/A                                      |
| No. of cases with multiple skin conditions (excluded from study) | 142             | 224              | N/A                                      |
| No. of cases indicated as not-diagnosable by dermatologists (excluded from study) | 271             | 165              | N/A                                      |
| No. of cases included in study                                | 16,114          | 3,756            | 963                                      |
| No. of images included in study                               | 64,837          | 14,883           | 3,707                                    |
| No. of patients included in study                             | 12,399          | 3,241            | 933                                      |
| Age\textsuperscript{a}, years: median (25th, 75th percentiles) | 40 (28, 54)     | 40 (28, 54)      | 43 (30, 56)                             |
| Female (%)                                                    | 10,014 (62.1%)  | 2,371 (63.1%)    | 615 (63.9%)                             |
| Race and ethnicity                                            |                 |                  |                                          |
| American Indian or Alaska Native (%)                          | 142 (0.1%)      | 42 (0.1%)        | 9 (0.9%)                                |
| Asian (%)                                                     | 1,775 (11.0%)   | 473 (12.6%)      | 97 (10.1%)                              |
| Black or African American (%)                                 | 1,087 (6.8%)    | 229 (6.1%)       | 61 (6.3%)                               |
| Hispanic or Latino (%)                                        | 7,044 (43.7%)   | 1,631 (43.4%)    | 409 (42.5%)                             |
| Native Hawaiian or Pacific Islander (%)                       | 224 (1.4%)      | 61 (1.6%)        | 19 (2.0%)                               |
| White (%)                                                     | 5,475 (34.0%)   | 1,175 (31.3%)    | 329 (34.2%)                             |
| Not specified (%)                                             | 367 (2.2%)      | 145 (3.9%)       | 39 (4.0%)                               |
| Fitzpatrick skin types (6 types)\textsuperscript{b}           |                 |                  |                                          |
| Type I (%)                                                    | 46 (0.3%)       | 9 (0.2%)         | 0 (0.0%)                                |
| Type II (%)                                                   | 2,807 (17.4%)   | 383 (10.2%)      | 104 (10.8%)                             |
| Type III (%)                                                  | 6,641 (41.2%)   | 2,412 (64.2%)    | 607 (63.0%)                             |
| Type IV (%)                                                   | 5,040 (31.3%)   | 724 (19.3%)      | 195 (20.2%)                             |
| Type V (%)                                                    | 510 (3.2%)      | 101 (2.7%)       | 24 (2.5%)                               |
| Type VI (%)                                                   | 46 (0.3%)       | 1 (0.0%)         | 0 (0.0%)                                |
| Unknown (%)                                                   | 1,024 (10.2%)   | 126 (3.4%)       | 33 (3.4%)                               |
| Skin conditions based on primary diagnosis (26 conditions, plus ‘other’):\textsuperscript{c} |                 |                  |                                          |
| Acne (%)                                                      | 1,645 (10.2%)   | 407 (10.8%)      | 40 (4.2%)                               |
| Actinic keratosis (%)                                         | 223 (1.4%)      | 53 (1.4%)        | 37 (3.9%)                               |
| Allergic contact dermatitis (%)                               | 173 (1.1%)      | 36 (0.9%)        | 25 (2.6%)                               |
| Alopecia areata (%)                                           | 323 (2.0%)      | 96 (2.5%)        | 37 (3.8%)                               |
| Androgenetic alopecia (%)                                     | 185 (1.1%)      | 50 (1.3%)        | 33 (3.4%)                               |
| Basal cell carcinoma (%)                                      | 285 (1.8%)      | 45 (1.2%)        | 28 (2.9%)                               |
| Cyst (%)                                                      | 279 (1.7%)      | 86 (2.3%)        | 31 (3.2%)                               |
| Eczema (%)                                                    | 2,368 (14.7%)   | 659 (17.5%)      | 50 (5.2%)                               |
| Folliculitis (%)                                              | 361 (2.2%)      | 87 (2.3%)        | 32 (3.3%)                               |
| Hidradenitis (%)                                              | 161 (1.0%)      | 45 (1.2%)        | 35 (3.6%)                               |
| Lentigo (%)                                                   | 113 (0.7%)      | 33 (0.9%)        | 32 (3.3%)                               |
| Melanocytic nevus (%)                                         | 792 (4.9%)      | 183 (4.9%)       | 34 (3.6%)                               |
| Melanoma (%)                                                  | 93 (0.6%)       | 22 (0.6%)        | 19 (1.9%)                               |
| Post inflammatory hyperpigmentation (%)                       | 162 (1.0%)      | 51 (1.4%)        | 29 (3.0%)                               |
| Psoriasis (%)                                                 | 1,983 (12.3%)   | 335 (8.9%)       | 39 (4.1%)                               |
| Squamous cell carcinoma/squamous cell carcinoma in situ (SCC/SCCIS) (%) | 148 (0.9%)      | 37 (1.0%)        | 33 (3.5%)                               |
| Seborrheic keratosis/irritated seborrheic keratosis (SK/ISK) (%) | 745 (4.6%)      | 211 (5.6%)       | 38 (4.0%)                               |
| Scar condition (%)                                            | 297 (1.8%)      | 60 (1.6%)        | 33 (3.4%)                               |
| Seborrheic dermatitis (%)                                     | 365 (2.3%)      | 98 (2.6%)        | 37 (3.8%)                               |
| Skin tag (%)                                                  | 239 (1.5%)      | 70 (1.9%)        | 33 (3.4%)                               |
| Stasis dermatitis (%)                                         | 124 (0.8%)      | 26 (0.7%)        | 25 (2.6%)                               |
| Tinea (%)                                                     | 229 (1.4%)      | 34 (0.9%)        | 31 (3.2%)                               |

Continued
We examined the importance of different the clinicians (range 0.27–0.71). alopecia, the DLS’s top-1 sensitivity of 0.82 was higher than that of for alopecia areata (0.84) was higher than for PCPs (0.56) and higher top-1 sensitivity than all clinicians (0.63 for the DLS versus 0.54 for PCPs and 0.49 for NPs) and comparable to the PCPs and NPs at identifying the infectious subcategory (0.71 for squamous skin diseases. The DLS had a higher top-1 sensitivity than versus non-infectious cases of erythematosquamous and papuloo-lysis distinguished between malignant versus benign growths. Note that, in this and subsequent subanalyses, the DLS and clinicians compared with the DLS across all 419 conditions are presented in Extended Data Fig. 2 and Supplementary Table 4.

Subgroup analysis. Next, we assessed the ability of DLS to distinguish between conditions that present similarly and can be misidentified in clinical settings (see the ‘Conditions in the subcategory’ column of Table 2 for definitions of the subgroups). The first analysis distinguished between malignant versus benign growths. Note that, in this and subsequent subanalyses, the DLS and clinicians could have determined the case as belonging to neither category (for example, neither a malignant nor a benign growth; that is, not a growth at all). Because the decision to biopsy depends on whether malignant conditions are in the differential, in this ‘growths’ subgroup analysis, we focused on the top-3 sensitivity for malignant growths. The DLS’s top-3 sensitivity of 0.90 was comparable with that of dermatologists (0.89) and higher than that of both PCPs and NPs (0.69 and 0.72, respectively; Table 2a). Similar trends were observed when restricting the analysis to cases with biopsy confirmation (Table 2b and Supplementary Table 5).

The second subgroup analysis distinguished between infectious versus non-infectious cases of erythematousquamous and papulosquamous skin diseases. The DLS had a higher top-1 sensitivity than the PCPs and NPs at identifying the infectious subcategory (0.71 for the DLS versus 0.54 for PCPs and 0.49 for NPs) and comparable to dermatologists. For the non-infectious subcategory, the DLS had a higher top-1 sensitivity than all clinicians (0.63 for the DLS versus 0.42–0.48 for clinicians).

The last subgroup deals with two types of hair loss: alopecia areata and androgenetic alopecia. The top-1 sensitivity of the DLS for alopecia areata (0.84) was higher than for PCPs (0.56) and NPs (0.48) and similar to dermatologists (0.84). For androgenetic alopecia, the DLS’s top-1 sensitivity of 0.82 was higher than that of the clinicians (range 0.27–0.71).

Importance of input data. We examined the importance of different input data to the DLS. Among the 45 types of non-image metadata (demographic information and medical history, see Supplementary Table 1), the type of self-reported skin problem (for example, acne, hair loss or rash) and history of psoriasis had the greatest impact on accuracy (Fig. 4a and Supplementary Fig. 3).

For image inputs, the performance of DLS improved dramatically when more than one image was provided and plateaued when there were at least five images (Fig. 4b, blue line). This trend was preserved when the non-image metadata were also withheld from the DLS (Fig. 4b, red line). Compared to withholding metadata from the DLS that was developed in the presence of metadata, training another DLS that uses only images (so it does not ‘rely’ on metadata) yielded a small improvement (Fig. 4b, green line). Finally, saliency analysis via integrated gradients highlighted those regions of the image where a skin condition was visible, suggesting the DLS had generally learned to focus on the correct region of interest when making the prediction (Fig. 3a–c).

We also examined the effect of training dataset size on the performance of the DLS and observed that more training data led to a better top-1 accuracy, though with diminishing return after 10,000 cases (Supplementary Fig. 4).

Discussion

In this study, we have developed and validated a DLS to identify 26 common skin conditions that were referred by primary care for a teledermatology consultation, representing ~80% of cases seen in primary care. The DLS’s top-1 diagnostic accuracy was non-inferior to dermatologists and higher than PCPs and NPs. Moreover, the DLS’s high top-3 accuracy and AO metric suggest that the DLS’s full differential diagnosis is relatively complete, and may help alert clinicians to differential diagnoses that they may not have considered. As a secondary prediction, the DLS also tackles a broader set of 419 skin conditions, with encouragingly similar results.

Providing assistance with a differential diagnosis instead of a single diagnosis is particularly important in dermatology. Because most skin conditions are not verified with pathology, the differential diagnosis is used for decision making around work-up and treatment. If all conditions in the differential diagnosis share the same treatment, a single diagnosis may not be clinically necessary. If the diagnoses on the differential have opposing treatments (for example, treatment for one condition on the differential may aggravate another diagnosis on the differential), a clinician can still consider this group of diagnoses together to determine a work-up or initiate treatment. In all these situations, the DLS may be an effective aid to non-specialists by helping them to arrive at both a
more accurate primary diagnosis and a more complete differential diagnosis. Dermatologists in ‘store-and-forward’ teledermatology (where dermatologists review cases asynchronously) could also potentially use such a DLS to help triage cases rapidly.

To better understand the impact of the DLS in specific challenging diagnostic situations, our subanalyses examined subgroups containing conditions with similar visual presentations and where distinguishing between conditions in different groups can affect subsequent clinical decisions. The three subgroup analyses were as follows: individual growths, erythematoussquamous and papulosquamous skin disease, and hair loss. For growths, malignant lesions should have subsequent biopsy or excision, whereas patients with benign lesions can be reassured. The top-3 sensitivity for malignant lesions is important because the inclusion of a diagnosis of malignancy on the differential diagnosis may prompt a clinician to obtain a specimen for pathology, even if it is not the primary suspected diagnosis. In erythematoussquamous and papulosquamous skin disease, these eruptions can be clinically similar to erythema and scaling, although they can have very different etiologies and treatment plans. An accurate diagnosis is particularly important, because first-line treatment of non-infectious entities is often with a topical steroid, which conversely would make an infectious process like tinea more resistant to treatment and can even hinder diagnosis (for example, tinea incognito) at future appointments. The inclusion of tinea as a potential diagnosis can also prompt a clinician to do a KOH exam for confirmation. For hair loss, the two conditions have different etiologies, possible work-up and treatment options. Distinguishing one from the other could allow a clinician to start first-line therapies and possible work-up for these conditions. In the first subgroup, the DLS was very ‘specific’; that is, it was able to correctly identify the ‘negative’ subcategory of benign growths. Despite a lower top-1 sensitivity for malignant lesions, the DLS had a high top-3 sensitivity, which is on par with dermatologists. For the second and third subgroups, the DLS had substantially higher sensitivities than non-specialists, suggesting that the DLS may be particularly valuable in helping determine the work-up or initiate treatment based on a working diagnosis.

Diagnostic uncertainty exists in our non-biopsied reference standard and dermatology more generally. Two conditions seemed particularly challenging based on low clinician accuracies (Extended Data Fig. 2). One condition was the presence of atopic dermatitis, which could be confused with psoriasis. The other was a skin eruption, which could be confused with urticaria. In both cases, the DLS was able to correctly identify the ‘negative’ subcategory of benign growths. Despite a lower top-1 sensitivity for malignant lesions, the DLS had a high top-3 sensitivity, which is on par with dermatologists. For the second and third subgroups, the DLS had substantially higher sensitivities than non-specialists, suggesting that the DLS may be particularly valuable in helping determine the work-up or initiate treatment based on a working diagnosis.
Data Fig. 1b) and inter-dermatologist agreement (Supplementary Table 6): allergic contact dermatitis (ACD) and post-inflammatory hyperpigmentation (PIH). Manual review of those cases by two other dermatologists showed that eight ACD cases were deemed clinically difficult because they lacked a ‘classic’ visual presentation. Additionally, despite guidance to be as specific as possible, some clinicians used the general term ‘contact dermatitis’, which also encompasses irritant contact dermatitis, which has different etiology, work-up and treatment interventions. This lack of specificity had prompted us to (a priori) categorize contact dermatitis under ‘Other’ and consider it ‘incorrect’. On the other hand, PIH was commonly ‘misdiagnosed’ due to attempts to label what the primary process leading to the PIH could have been. To ensure that these complexities did not cause our DLS evaluations to be overly optimistic, we recomputed the sensitivities excluding these two conditions for the DLSs and all clinicians (Supplementary Table 7), finding small improvements for both the DLS and clinicians, with no change in conclusions. We also repeated the analysis on cases with less diagnostic ambiguity (that is, where two or three of the reference standard dermatologists agreed on the primary diagnosis) and observed similar results (Supplementary Figs. 5 and 6).

Our study showed that dermatologists were substantially more accurate than PCPs and NPs. The finding was not surprising, as the majority of the cases were sent by primary care providers to a teledermatology service, and presumably the clinician had found them difficult to diagnose. Although not strictly comparable because of differences in study design, the low accuracies we observed (35–49%, Supplementary Table 8) are in line with those previously reported (24–70%). These numbers serve to highlight the challenging nature of this classification task that incorporates both visual and non-visual information, and underscores the need for decision support tools for non-specialists.

Previous studies in this area generally have not focused on providing diagnostic assistance in a more generalized workflow, but instead have focused on early screening of skin cancer and thus were limited to a narrower scope of conditions (for example, melanoma or not) or on more standardized images that require specialized equipment (that is, dermoscopic images). Of the studies that attempted to tackle a broader range of conditions, the datasets were often either educational in nature, leading to potential bias towards cases with more typical presentations or unusually severe cases that prompted pathologic confirmation, or a simplification of labels towards a mix of morphological descriptions.

**Fig. 3** Representative examples of challenging cases missed by non-dermatologists. For each case, an original image is provided on the left and an image with a saliency mask on the right. The middle image shows the original image, with the saliency overlay in green. All clinicians were instructed to be as specific as possible when providing the diagnostic labels. Diagnoses for the reference standard and comparator clinicians who reviewed each case are included here and ranked by confidence from top to bottom. a. The DLS’s primary diagnosis of basal cell carcinoma (BCC) concurs with the reference standard, both comparator dermatologists and one PCP. Both NPs and one PCP missed this diagnosis. b. The DLS’s primary diagnosis of squamous cell carcinoma (SCC/SCCIS) concurs with the reference standard and both comparator dermatologists. Both NPs considered another diagnosis as more or equally likely, while the PCPs missed this diagnosis. c. The DLS’s primary diagnosis of tinea concurs with the reference standard and primary diagnoses of the comparator dermatologists. One PCP considered another diagnosis as equally likely, while the other PCP and both NPs missed this diagnosis. d. The DLS, comparator dermatologists and one PCP all agreed with the reference standard of alopecia areata (AA). This was missed as a primary diagnosis by both NPs and one of the PCPs. e. The DLS’s primary diagnosis of androgenetic alopecia (AGA) concurs with the reference standard and both comparator dermatologists. This was missed as a primary diagnosis by both NPs and both PCPs. In the last two cases (d, e), diagnosing the specific type of alopecia is important because AGA and AA have different treatments. More details about these cases are presented in Supplementary Fig. 2.
(for example, erythema/"redness") and specifications too broad to guide clinical next steps (for example, hair loss without further details)\(^3\). As a result, the utility of these works in actual clinical settings is unclear. By contrast, the images in our data were taken by medical assistants across 17 sites, representing a wide variety of lighting conditions, perspectives and backgrounds. Our dataset is also representative of cases that require dermatology consultations, and the conditions that our DLS predicts are specific enough to guide a clinician to the next steps in clinical care. However, due to the impracticality of performing exhaustive tests or biopsies for all skin conditions, there exists inevitable diagnostic uncertainty in actual clinical settings. To help resolve this, our DLS learns to predict a differential diagnosis instead of a single diagnosis, enabling a decision support tool that surfaces potential diagnoses for clinicians to consider.

Our DLS can potentially augment the current clinical workflow in a primary-care setting in several ways. First, the DLS can prompt clinicians to include on their differential a diagnosis that they would not have considered previously, particularly for difficult cases that they might have otherwise referred. Our data (Fig. 2c,d) suggest that clinicians could identify low-confidence cases and leverage the DLS’s higher accuracy on those cases. This applies to most NPs in this study, regardless of confidence level, while all PCPs would have benefited at confidence ≤ 4. The DLS may thus prevent misdiagnosis, delay to care, and improper treatment, which can lead to poor clinical outcomes, a bad patient experience and increased costs of care. Second, by helping to improve the accuracy of non-dermatologists, the referrals to dermatologists may be more appropriate. With challenges to access, it is important to identify referred cases as urgent versus non-urgent. If the non-dermatologist clinician provides a more accurate diagnostic assessment at the time of referral, the patient can be more appropriately triaged for an appointment.

From a technical aspect, while most previous work used a single image as input, our DLS integrates information from both metadata and multiple images. We further quantify the magnitude of improvement as metadata or more images are provided for each case. Similarly, dermatologists in a teledermatology setting look at multiple images to better appreciate the three-dimensional and textural aspects of the skin findings. We also show that visual features alone enable reasonable diagnostic accuracy by the DLS, and accuracy improves with more images, albeit with diminishing returns. This has implications for broader real-world usage: a single image is likely to be suboptimal, but more than five provides marginal benefit. Adding metadata provides another 4–5% improvement, with most of the benefit coming from a handful of features. Thus, a few questions may be sufficient to capture most of the diagnostic accuracy benefits. Moreover, even the most ‘important’ metadata (the type of self-reported skin problem) caused a small 0.8% reduction in top-1 accuracy when permuted (see Methods), suggesting robustness of the DLS to metadata error.

Our study has limitations. First, we lacked a completely external dataset for validation, but instead split the data temporally. This mimics developing a DLS using retrospective data and then validating that DLS at the same sites on data collected over the next year. To aid generalization beyond the specific metadata in this dataset, we also trained a version of the DLS that uses only images as input (Fig. 4b), which may be more easily applicable to practices without or with different metadata. Second, our data did not include additional testing, and only a subset of suspected malignancies had biopsy confirmation. Instead, our reference standard for each case was based on aggregating the differential diagnoses of a panel of non-dermatologists.

### Table 2: Sensitivity of the deep learning system (DLS) and three types of clinician (dermatologist, primary care physician and nurse practitioner) for clinically relevant and challenging subgroups based on appearance on clinical presentation

| Clinically relevant groups | Subcategory | Conditions in the subcategory | No. of cases | Top-1 sensitivity | Top-3 sensitivity |
|---------------------------|-------------|-------------------------------|--------------|------------------|------------------|
|                           | Growth      | Malignant BCC, melanoma, SCC/SCCIS | 83           | 0.57 0.74 0.52   | 0.90 0.89 0.69   |
|                           |             | Actinic keratosis, cyst, lentigo, melanoctytic nevus, SK/ISK, skin tag, verruca vulgaris | 178         | 0.74 0.66 0.56   | 0.92 0.76 0.70   |
|                           | Erythematous and papulosquamous skin disease | Infectious Tinea, tinea versicolor | 66          | 0.71 0.72 0.54   | 0.88 0.85 0.70   |
|                           |             | Non-infectious Eczema, psoriasis, stasis dermatitis, allergic contact dermatitis, seborrheic dermatitis | 202        | 0.63 0.42 0.48   | 0.92 0.55 0.62   |
|                           | Hair loss   | Alopecia areata | 37          | 0.84 0.84 0.56   | 0.86 0.91 0.77   |
|                           |             | Androgenetic Alopecia | 34          | 0.82 0.71 0.30   | 0.97 0.84 0.43   |

(a) Performance relative to the dermatologists-determined reference standard. (b) Performance relative to a biopsy-determined reference standard (where available). Distributions of biopsy cases are reported in Supplementary Table 5. Bold indicates the highest value for each subcategory and each evaluation metric. APPV, positive predictive value of cases predicted or diagnosed to have a malignant skin disease.

For validation, we used two datasets:

- **Validation set A** (52 malignancies out of \(n=100\) cases)
- **Validation set B** (enriched subset of set A; 37 malignancies out of \(n=53\) cases)

| | Sensitivity | PPV\(^a\) |
|---|---|---|
| Top-1 DLS DLS DLS | 0.48 0.96 | 0.57 0.74 0.58 0.55 0.95 | 0.85 0.86 0.88 |
| Top-3 DLS DLS DLS | 0.88 0.69 | 0.92 0.89 0.81 0.73 0.76 0.81 0.86 0.84 |

\(^a\) Performance relative to a biopsy-determined reference standard (where available).
In principle, multiple conditions may be handled as several useful, it is less rich than free text clinical notes or an in-person de-identified, only structured metadata were available. Although rashes, which are not typically biopsied. Third, as our dataset was do exist in clinical practice, which makes it challenging to evaluate the ranges and outliers are defined by 1.5 times the interquartile range.

Online content
Any methods, additional references, Nature Research reporting summaries, source data, extended data, supplementary information, acknowledgements, peer review information; details of author contributions and competing interests; and statements of data and code availability are available at https://doi.org/10.1038/s41591-020-0842-3.

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Methods

Dataset. The dataset for this study consisted of retrospective consecutive adult cases from a teledermatology service serving 17 primary-care and specialist sites from two states in the United States. Cases were predominantly referred by medical doctors, doctor of osteopathic medicine, NPs and physician assistants. Each case contained one and six clinical photographs of the affected skin areas taken by medical assistants or trained nurses (~75% of cases had six or fewer images; for cases with more images, six images were randomly selected). Images were taken on a mix of devices (Canon point-and-shoot cameras and Apple iPad Mini).

Each case also contained metadata such as patient demographic information and medical history (for a complete list see Supplementary Table 1), which were available to both the DLS and all clinicians in this study. Histology (biopsy) was only done in a small number of patients, reflecting the daily routine in dermatology. All images and metadata were de-identified according to the Health Insurance Portability and Accountability Act (HIPAA) Safe Harbor before transfer to study investigators. The protocol was reviewed by Advarra IRB, which determined that it was exempt from further review under 45 CFR 46.

The dataset was split in a 80:20 ratio based on the submission date of the case: the development set contained cases from 2010–2017, while the validation set contained cases from 2017–2018 (Table 1). Such a temporal split strategy helps simulate a study where a model is developed on past data and validated on future cases, and is arguably a form of external validation46. An anonymous patient ID was used to ensure that no patients overlapped between the development set and the validation set, thus preventing any potential label leakage due to the presence of cases labelled by the same dermatologist (Supplementary Fig. 6). This validation set was further subsampled to reduce class imbalance among the skin conditions of interest to obtain validation set B (Table 1). Selection of skin conditions is described in the section ‘Labeling tool and skin condition mapping’.

Reference standard labeling validation set. Because of the impracticality of pathologic confirmation of all diagnoses (for example, rashes are rarely biopsied), each case's differential diagnosis for the validation set was provided by a rotating panel of three dermatologists from a pool of 14 US board-certified dermatologists. The dermatologists practiced in multiple states (Colorado, Hawaii, Iowa, Massachusetts, New York, South Carolina, Tennessee and Texas) and participated in the study via Advanced Clinical. None of the dermatologists were actively practicing teledermatology, although some may have had prior experience or training (for example, during residency); nine were in private or group practice; three were in private practice with concurrent academic appointments; two had primary academic affiliations. They had 5–30 years of experience (average 9.1 years, median 6.5 years) and were actively seeing patients in clinic. The dermatologists also passed a certification test on a small number of cases to ensure that they were comfortable with grading cases using the labeling tool (Supplementary Table 9 and Supplementary Fig. 7). Every dermatologist graded each case (clinical photographs, demographic information and medical history) independently for the presence of multiple skin conditions, diagnosability (for example, due to poor image quality, mixture of pathology or limited field of view) and up to three differential diagnoses using a custom annotation tool (see ‘Labeling tool and skin condition mapping’ and Supplementary Figs. 8 and 9). Cases labeled as containing multiple skin conditions or as undiagnosable by the majority of the dermatologists were excluded from the study.

Because individual graders can demonstrate substantial variability, to determine the reference standard we aggregated the differential diagnoses of the three dermatologists that reviewed each case based on a previously proposed ‘voting’ procedure27 (see Supplementary Methods for details and Supplementary Fig. 10 for an example). Briefly, for each grader, each diagnosis was first mapped to one of 419 conditions (see ‘Labeling tool and skin condition mapping’), then duplicated, unaccented condition names were removed. Votes for each of these mapped conditions were summed across the three dermatologists based on the relative position of each diagnosis within each dermatologist's differential. The final differential was thus based on the aggregated votes across three board-certified dermatologists.

We verified that this procedure provides substantially higher reproducibility in differential diagnoses than between individual dermatologists (0.77 versus 0.66; for more details see Supplementary Methods). The distribution of the top differential diagnoses is presented in Table 1.

Reference standard labeling development set. The development set was further split into a training set to ‘learn’ the neural network weights and a testing set to select hyperparameters for the training process. To maximize the amount of training data, more dermatologists labeled the development set: 1–39 dermatologists (from a cohort of 37 US board-certified and five Indian board-certified dermatologists) labeled each case (mean number of dermatologists per case 4.0, standard deviation 2.6). This range was a result of dispatching reviews on a rolling basis to accelerate reviews and does not reflect the difficulty of cases. Only cases considered by all of the dermatologists grading that case as having multiple skin conditions or undiagnosable were discarded. Reference standard differential diagnosis was established in the same way as for the validation set.

Labeling tool and skin condition mapping. Our labeling tool provided a search-as-you-type interface (Supplementary Table 9 and Supplementary Fig. 7) based on the standardized Systematized Nomenclature of Medicine–Clinical Terms (SNOMED-CT)49, with more than 20,000 conditions related to cutaneous disease. If the dermatologist could not find a matching SNOMED-CT term, the diagnosis could be entered as free text.

Because SNOMED-CT contains terms at varying granularities and there are complex and incompletely specified relationships between terms23, three board-certified dermatologists mapped these terms and free text diagnoses entries to a list. The list was initially populated with dermatologic conditions that were common or high-acute, and more conditions were added as needed. Considerations during this mapping were a granularity that would (1) allow a non-dermatology clinician to reasonably determine the next steps in clinical care, (2) enable clear and concise communication with another healthcare provider and (3) exclude superfluous information for most purposes (for example, specific site of the condition). For example, a diagnosis such as ‘alopecia’ would be too broad, but ‘alopecia areata’ and ‘androgenetic alopecia’ would allow a non-dermatologist to engage in the next steps in clinical care.

As labels for cases were collected, additional conditions were added to the list, as appropriate, based on the discussion of at least two of the three dermatologists. Some diagnoses were marked as invalid if they were too broad, non-skin entries, reflected multiple skin conditions (such as a syndrome with multiple skin findings) or were semantically unclear (for example, tooth abrasion). All mappings and labeling were performed while blinded to DLS predictions. The final list contained 419 conditions (Supplementary Table 10).

Selection of the 26 skin conditions. As in actual clinical practice, the prevalence of different skin conditions was heavily skewed in our dataset, ranging from skin conditions with >10% prevalence like acne, eczema and psoriasis to those with sub-1% prevalence like lentigo, melanoma and stasis dermatitis. To ensure that there was sufficient data to develop and evaluate the DLS, we focused on the 26 skin conditions with the top 26 with the highest prevalence based on the development set (when the labeling was ~80% complete). Specifically, this ensured that, for each of these conditions, there were at least approximately 100 cases in the development set (for DLS training purposes) and a projected 25 cases in the validation set (for DLS evaluation). The remaining conditions were aggregated into an ‘Other’ category (which comprised 21% of the cases in validation dataset A).

DLS development. The DLS has two main components, an image-processing deep convolutional neural network and a shallow network that processes clinical metadata (demographic information and medical history). The image-processing component consisted of a variable number (1–6, depending on the number of images in each case) of Inception-v453 modules with shared weights. All images were resized to 459×459 pixels, the default size of this network architecture. The clinical metadata were featureized using the one-hot encoding for all categorical features. Age was used as a number normalized to [0,1] based on the range in the development set. These two components were joined at the top using a fully connected layer (that is, late fusion)22. The DLS did not have access to any other clinician-provided diagnoses as input.

To help the DLS learn to predict a differential diagnosis (as opposed to a pure classification to predict a single label), the target label of the DLS was based on each case's reference standard differential diagnosis. Specifically, the summed ‘votes' of each condition in the differential were normalized (to sum to 1), and the DLS was trained using a softmax cross-entropy loss to learn these ‘soft' target labels. To account for class imbalance, when calculating cross-entropy loss, each class was weighted as a function of its frequency, so that cases of rare conditions would contribute more to the loss function. The network weights were optimized using a distributed stochastic gradient descent implementation that predicted both the full list of 419 conditions and the shorter list of 27 conditions (26 conditions plus 'Other'). To speed up the training and improve training performance, batch normalization20 and pre-initialization from ImageNet dataset were used21. Training was stopped after a fixed number of steps (100,000) with a batch size of 8. To train the DLS, the development set was partitioned into a training set to learn DLS's parameters and a tuning set to tune hyperparameters. Because of the severe class imbalance, we created the tune set via stratified sampling (of up to 50 cases per condition). To ensure a clean split with respect to patients, all cases from the patients represented in this sampling were moved to the tune set.

Data augmentation was applied to improve generalization (random flipping, rotating, cropping and color perturbation). The random cropping was parameterized to ensure that the crops had a minimum overlap of 20% with the pathologic skin region (a separately collected label for every case in the training set). Random dropout was applied to metadata features (assigned to unknown), to help improve robustness to missing values or potential data errors. Six networks were trained with the same input and hyperparameters (see Supplementary Table 11 for a complete list of hyperparameters) and ensembled22 to provide the final prediction.

DLS evaluation. To evaluate the DLS performance, we compared its predicted differential diagnosis with the ‘voted' reference standard differential diagnosis.
using the top-k accuracy and the average top-k sensitivity. The top-k accuracy measures how frequently the top k predictions capture any of the primary diagnoses in the reference standard (that is, ranked first in the differential). The top-k sensitivity assesses this for each of the top k conditions separately, whereas the final average top-k sensitivity is the average across the 26 conditions.

Averaging across the 26 conditions avoids biasing towards more common conditions, particularly in validation set A. We use both the top-1 and top-3 metrics in this study.

In addition to comparing both the DLS and clinicians against the voting-based reference standard differential diagnoses, we also evaluated against a reference standard based on agreeing with ‘at least one’ of the three board-certified dermatologists comprising the reference standard (Accuracy57,58, Supplementary Tables 8, 12 and 13).

Finally, we also measured the agreements in the full differential diagnosis between the DLS and reference standard using the AO metric57,58. Because the clinicians were instructed to provide up to three diagnoses, we similarly filtered the DLS's predictions to retain the top-3. Next, unlikely diagnoses lower than a predicted likelihood of 0.1 (selected based on the AO computed on the tune dataset) were filtered to produce the final DLS-predicted differential (up to three diagnoses in ranked order).

Comparison to clinicians. To compare the DLS performance with clinicians, a group of 18 clinicians (who did not participate in earlier parts of this study) provided differential diagnoses for validation set B. These clinicians were composed of three groups of six US board-certified clinicians (dermatologists, PCPs, and NPs) and participated in the study via Advanced Clinical. The dermatologists included both academic and private-practice physicians, and all PCPs and NPs were employed in a private practice or medical group and recruited through Advanced Clinical or referrals. In terms of state of practice, the dermatologists practiced in the states of California, Georgia, Maryland, New York, and Tennessee and the PCPs and NPs in Arizona, California, Colorado, Connecticut, Florida, Illinois, New York, South Dakota, Vermont and Washington. All clinicians were compensated at an hourly rate comparable to market rates.

One dermatologist had prior teledermatology experience, and the others may have had prior training (for example, as part of residency). The NPs were selected from those who were practicing independently as primary-care providers without physician supervision. Every clinician graded a random one-third of the cases, and each case was graded by two random clinicians from each group (six clinicians in total). These clinicians used the same labeling tool as the dermatologists involved in determining the reference standard, and their diagnoses were mapped and processed similarly. There was no time constraint. In case of ties, the top-4 diagnoses were determined by randomly selecting the diagnosis from the tied candidates. This tie-breaking affected the top-1 analyses for 13% of dermatologist-provided, 24% of PCP-provided and 14% of NP-provided diagnoses. The top-3 analysis was minimally affected, with no ties from dermatologists and NPs and 0.6% ties from PCPs. This tie-breaking avoided confounding the analysis by biasing towards clinicians who provided tied differential diagnoses (which indicates uncertainty).

Feature importance. Additionally, we investigated the relative importance of different types of input on DLS performance. To study the effect of the number of images, we selected a subset of the images for each case to measure DLS performance on this subsampled dataset. For the clinical metadata, we used a permutation procedure (‘permutation feature importance’55). Briefly, for a metadata variable of interest, this procedure randomly permutes its assignment across cases in validation set A. Next, the performance of the DLS was measured using the perturbed dataset. To understand the importance of all the metadata collectively, we dropped out all the metadata by assigning all their values to unknown. Because the network could have been dependent on metadata in this analysis, thus over-representing the importance of metadata, we further trained a DLS using only images and evaluated its performance. Finally, we used integrated gradients54 to highlight the parts of each image that have the biggest effect on the prediction.

Statistical analysis. To compute the confidence intervals, we used a non-parametric bootstrap procedure56 with 1,000 samples. Because of the intensive computation required to re-run DLS inference, confidence intervals for the feature importance analyses were calculated using the normal approximation with 20 runs (1.96 x standard error, with each run performed on the entire validation set A). To compare the DLS performance to clinicians, a standard one-tailed permutation test55 was used. Briefly, in each of the 10,000 trials, the DLS's score was randomly swapped with itself or a comparator clinician's score for each case, yielding a DLS–human difference in top-1 accuracy sampled from the null distribution. To perform the non-inferiority test, the empirical P value was computed by adding the 5% margin to the observed difference and comparing this number to its empirical quantiles55,56. Non-inferiority compared to dermatologists in top-1 accuracy was determined by biasing towards clinicians who provided tied differential diagnoses (which indicates uncertainty).

| Reporting Summary. Further information on research design is available in the Nature Research Reporting Summary linked to this Article. |

Data availability
The de-identified teledermatology data used in this study are not publicly available due to restrictions in the data-sharing agreement.

Code availability
The deep learning framework (TensorFlow) used in this study is available at https://www.tensorflow.org/. The training framework (Estimator) is available at https://www.tensorflow.org/guide/estimators. The deep learning architecture (Inception-v4) is available at https://github.com/tensorflow/models/blob/master/research/slim/nets/inception_v4.pb.

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Author contributions
Yuan Liu, A.J., C.E., D.H.W., K.L. and D.C. prepared the dataset for usage. S.J.H., K.K. and R.H.-W. provided clinical expertise and guidance for the study. Yuan Liu, A.J., C.E., K.L., P.B., G.D.O.M., J.G., D.A., S.J.H. and K.K. worked on the technical, logistical and quality control aspects of label collection. S.J.H. and K.K. established the skin condition mapping. Yuan Liu, K.L., V.G. and D.C. developed the model. Yuan Liu, A.J., N.S. and V.N. performed statistical analysis and additional analysis. Yun Liu guided study design, analysis of the results and statistical analysis. S.G. studied the potential utility of the model. R.C.D. and D.C. initiated the project and led the overall development, with strategic guidance and executive support from G.S.C., L.H.P. and D.R.W. Yuan Liu, Yun Liu and S.J.H. prepared the manuscript with the assistance and feedback from all other co-authors. K.K. and S.J.H. performed the work at Google Health via Adecco Clinical. G.d.O.M. performed the work at Google Health via Adecco Staffing. N.S. performed the work at Google Health.

Competing interests
K.K. and S.J.H. were consultants of Google LLC. R.H.-W. is an employee of the Medical University of Graz. G.d.O.M. is an employee of Adecco Staffing supporting Google LLC. This study was funded by Google LLC. The remaining authors are employees of Google LLC.
LLC and own Alphabet stock as part of the standard compensation package. Yuan Liu, A.J., C.E., D.H.W., K.L., P.B., J.G., V.G., D.A., Yun Liu, R.C.D. and D.C. are inventors on a filed patent related to this work. The authors declare no other competing interests.

**Additional information**
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Extended Data Fig. 1 | Performance of the deep learning system (DLS) and clinicians, broken down for each of the 26 categories of skin conditions and ‘other’. a, Top-1 and top-3 sensitivity of the DLS on validation set A (n=3,756). b, Top-1 and top-3 sensitivity of the DLS and three types of clinicians: dermatologists (Derm), primary care physicians (PCP), and nurse practitioners (NP) on validation set B (n=963). Numbers in parentheses in the x-axes indicate the number of cases. Detailed breakdown of each clinician and the DLS performance on the subset of cases graded by each clinician are in Supplementary Table 8. Error bars indicate 95% CI (see Statistical Analysis).
Extended Data Fig. 2 | Performance of the deep learning system (DLS) and the clinicians on the 419-way classification: dermatologists (Derm), primary care physicians (PCP), and nurse practitioners (NP) on validation set A (n=3,756) and validation set B (n=963). a, Top-1 and top-3 accuracy for the DLS and clinicians across all cases and 419 categories of skin conditions. b, Average overlap (to assess the full differential diagnosis) of the DLS and clinicians. Error bars indicate 95% confidence intervals (see Statistical Analysis).
Reporting Summary

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- For Bayesian analysis, information on the choice of priors and Markov chain Monte Carlo settings
- For hierarchical and complex designs, identification of the appropriate level for tests and full reporting of outcomes
- Estimates of effect sizes (e.g. Cohen’s d, Pearson’s r), indicating how they were calculated

Our web collection on statistics for biologists contains articles on many of the points above.

Software and code

Policy information about availability of computer code

Data collection: Data from a Teledermatology service were de-identified prior to transfer to study investigators.

Data analysis: The deep learning framework (TensorFlow v.1.15.0) used in this study is available at https://www.tensorflow.org/; the training framework (Estimator) is available at https://www.tensorflow.org/guide/estimators; the deep learning architecture (Inception-v4) is available at: https://github.com/tensorflow/models/blob/master/research/slim/nets/inception_v4.py.

For manuscripts utilizing custom algorithms or software that are central to the research but not yet described in published literature, software must be made available to editors/reviewers. We strongly encourage code deposition in a community repository (e.g. GitHub). See the Nature Research guidelines for submitting code & software for further information.

Data

Policy information about availability of data

All manuscripts must include a data availability statement. This statement should provide the following information, where applicable:

- Accession codes, unique identifiers, or web links for publicly available datasets
- A list of figures that have associated raw data
- A description of any restrictions on data availability

The de-identified teledermatology data used in this study are not publicly available due to restrictions in the data-sharing agreement.
Field-specific reporting

Please select the one below that is the best fit for your research. If you are not sure, read the appropriate sections before making your selection.

☒ Life sciences □ Behavioural & social sciences □ Ecological, evolutionary & environmental sciences

For a reference copy of the document with all sections, see nature.com/documents/nr-reporting-summary-flat.pdf

Life sciences study design

All studies must disclose on these points even when the disclosure is negative.

Sample size
The 80:20 development/validation split was determined a priori without sample size calculations. The number of skin conditions (26) was chosen such that at least 100 examples per skin condition (based on preliminary labels) would be available for model development, and a projected 25 examples per skin condition for model validation.

Data exclusions
Several pre-determined exclusion criteria were applied. First, cases with multiple skin conditions or not diagnosable were excluded from the study. Second, from the validation sets, cases from repeat visits of a patient in the development dataset were excluded to avoid bias.

Replication
The deep learning system is an ensemble of 6 trained models. The spread in tuning set performance between the 6 trained models was measured at 1-3%.

Randomization
Validation set B cases were randomly subsampled from validation set A using stratified random sampling to enrich for rarer skin conditions.

Blinding
The skin condition mapping were established by dermatologists who were blinded to the predictions of the deep learning system.

Reporting for specific materials, systems and methods

We require information from authors about some types of materials, experimental systems and methods used in many studies. Here, indicate whether each material, system or method listed is relevant to your study. If you are not sure if a list item applies to your research, read the appropriate section before selecting a response.

| Materials & experimental systems | Methods |
|----------------------------------|---------|
| n/a □ Involved in the study      | n/a □ Involved in the study |
| ☒ □ Antibodies                   | ☒ □ ChIP-seq |
| ☒ □ Eukaryotic cell lines        | ☒ □ Flow cytometry |
| ☒ □ Palaeontology                | ☒ □ MRI-based neuroimaging |
| ☒ □ Animals and other organisms  |         |
| ☒ ☒ Human research participants  |         |
| ☒ □ Clinical data                |         |

Human research participants

Policy information about studies involving human research participants

Population characteristics
De-identified data from cases submitted to a teledermatology service. Baseline variables are reported in Table 1, but briefly on the development and validation sets, patients were aged 40-43 on average, with 62-64% female, and the most common diagnoses were eczema, psoriasis, and acne. Post-visit treatment data were not available.

Recruitment
All consecutive adult cases in the time period (2010-2018) were used, excluding those with multiple skin conditions or not diagnosable (as in exclusion criteria above).

Ethics oversight
The protocol was reviewed by Advanta IRB (Columbia, MD), which determined that it was exempt from further review under 45 CFR 46.

Note that full information on the approval of the study protocol must also be provided in the manuscript.