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INVESTIGATIVE REPORT

Utility of Non-rule-based Visual Matching as a Strategy to Allow Novices to Achieve Skin Lesion Diagnosis

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Non-analytical reasoning is thought to play a key role in dermatology diagnosis. Considering its potential importance, surprisingly little work has been done to research whether similar identification processes can be supported in non-experts. We describe here a prototype diagnostic support software, which we have used to examine the ability of medical students (at the beginning and end of a dermatology attachment) and lay volunteers, to diagnose 12 images of common skin lesions. Overall, the non-experts using the software had a diagnostic accuracy of 98% (923/936) compared with 33% for the control group (215/648) (Wilcoxon $p < 0.0001$). We have demonstrated, within the constraints of a simplified clinical model, that novices' diagnostic scores are significantly increased by the use of a structured image database coupled with matching of index and referent images. The novices achieve this high degree of accuracy without any use of explicit definitions of likeness or rule-based strategies. ***Key words: non-analytical reasoning; skin cancer; electronic clinical decision support software; melanoma; dermatology diagnosis.***

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Understanding the cognitive skills involved in making a dermatological diagnosis may be important both for improving the education of doctors, whether specialists or generalists, and for enabling patients to detect early signs of skin disease. In this regard, and in the rest of this paper, we are considering in particular skin cancer and lesions that might be confused with skin cancer.

Despite the importance of the topic to dermatological practice there is only a handful of papers concerned with the psychological processes involved in dermatological diagnosis, notably those of Geoff Norman and colleagues (1–7). At the risk of some simplification, the processes involved in diagnosis can be viewed either as being explicit and based on conscious reasoning, or as being implicit, holistic and hidden from the conscious view of the diagnostician (8). This distinction in certain respects corresponds to the division between Type 1 and Type 2 decision-making highlighted by Kahneman (for review see Evans (8)). For example, in diagnosing a nodular basal cell carcinoma a clinician might state that he or she applies a set of rules, such as the presence of a pearly edge, telangiectasia and so on, or alternatively might "at a glance" recognize features holistically that, from previous experience and learning, are characteristic of a basal cell carcinoma. Whilst in reality it seems likely that different processes might be used in different clinical situations, there is good evidence that much clinical reasoning and other forms of expertise is indeed holistic and that the clinician may not be privy as to how he or she achieves the correct diagnosis (9–11). In the particular context of some medical expertise this form of reasoning has been labelled by Norman as "non-analytical reasoning" (2, 4, 5).

One issue raised by such insights is whether it is possible to build tools that might enhance non-analytical strategies, such that, rather than apply explicit rules (e.g. the ABCD rules for melanoma diagnosis (12)), novices or learners might be able to match index cases with a database of images in order to achieve a diagnosis (or at least narrow the range of diagnostic uncertainty). In our experience many clinicians are very sceptical that such an approach might be useful. There is, however, some tentative evidence that such a matching strategy may work, although only to the extent that it has been demonstrated to be better than chance (13).

A scalable vehicle in which to examine the utility of matching is by use of World Wide Web (WWW) browser-based interfaces written in HTML/JAVA code. The WWW allows large numbers of images to be distributed at low cost and lends itself to the addition of computational engines that might, at a later date, allow a range of clinical variables to be added to enhance the possibility of success. Therefore, in the present study we set out to examine experimentally whether non-experts can use a simple bespoke JAVA test interface to match index cases presented as a digital image with a range of images including those from the correct diagnostic class. In order to provide a reference level of competence we compared the results of such an approach with the diagnostic accuracy of a control group of medical students before and after a dermatological attachment.

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MATERIALS AND METHODS

Software image selection

Eighty images from 5 diagnostic classes of commonly referred focal skin lesions were selected from the University of Edinburgh Dermatology Department's image library. The images comprised 14 haemangiomas, 23 seborrhoeic keratoses, 19 melanocytic naevi, 15 basal cell carcinomas and 9 squamous cell carcinomas. Images were chosen on the basis of technical quality and because they were considered to be representative of a particular diagnostic class. These 5 diagnostic groups comprise the majority of the lesions that are referred from primary care for specialist assessment. All the images had been collected using the same controlled fixed-distance photographic set-up; Canon (Canon UK Ltd, Reigate, Surrey, UK) EOS 350D 8.1MP cameras, Sigma (Sigma Imaging UK Ltd, Welwyn Garden City, Hertfordshire, UK) 70-mm f2.8 macro lens and Sigma EM-140 DG Ring Flash at a distance of 50 cm. From these 80 images, 12 index lesions were randomly selected, with the remaining 68 images acting as referent images in the software image database.

Software design

Our prototype software allows the user to make a direct visual comparison between a centralized index image and up to 12 surrounding referent images (Fig. 1). The user then navigates through the library of referent images until they are satisfied that they have successful matched the index lesion to a similar referent image (or images). In this experiment the 68 referent images were arranged over 3 levels utilizing a total of 18 different screens (1 screen for level 1, 5 screens for level 2, and 12 screens for level 3). Irrespective of which index image was being tested, the referent images in the first level's screen were identical for all matching attempts. It was only the subsequent second and third level screens' referent images that were determined by the individual user's image selection. The order in which these 5 second-level and 12 third-level screens were displayed and their relationship to a specific user's image selection was predetermined by the experimenters and was kept constant for the duration of the experiment. The method employed for grouping the 68 images to the 18 screens and the relationship of a screen to a specific user interaction was based on the experimenters' opinion of visual similarity and, to a lesser degree, the lesions' underlying pathological diagnosis. If the user was unhappy with their selection at any stage of the process (prior to confirming their final match) the software allowed them to retrace their steps. As the screenshots attest, the software is very intuitive; nonetheless, to demonstrate how to navigate through the software library and how to make a final diagnostic match we integrated a short instructional video into the software. This video, to avoid any potential bias, did not include images of skin lesions but demonstrated the key features of the software using simple pictures of differing shapes (circles, squares, crosses). A video demonstrating the version of the software tested is available on YouTube (Google, CA, USA) (14).

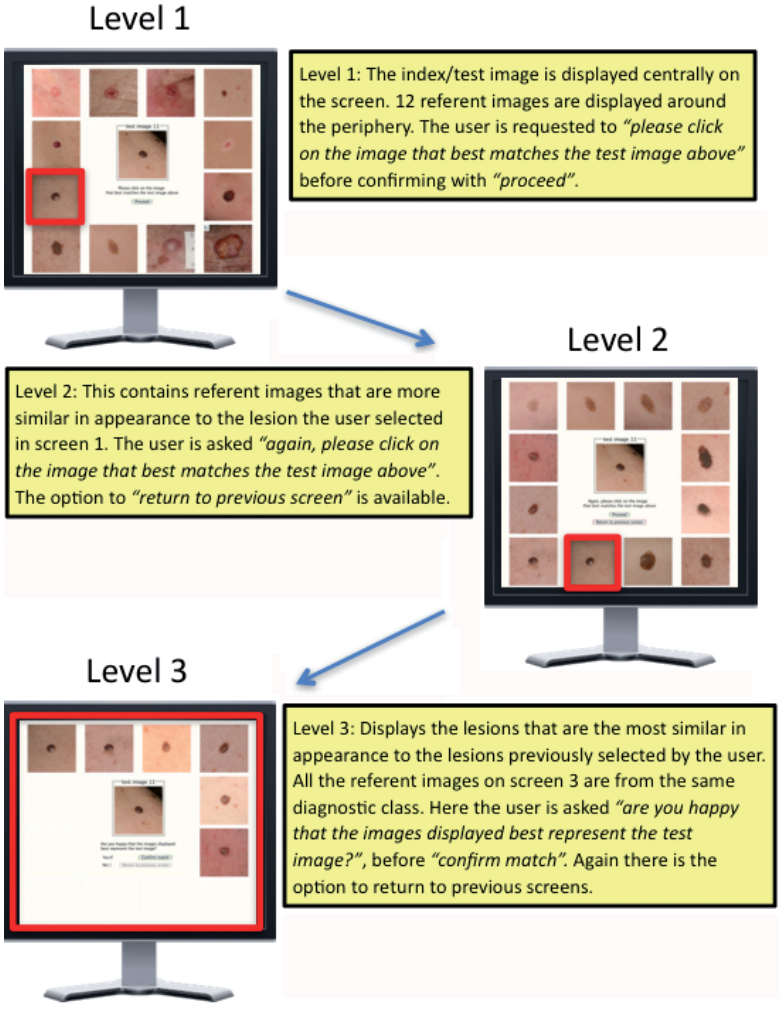

Fig. 1. Screenshots from the software showing how a correct diagnostic match could be made for index/test image 11 (a seborrhoeic keratosis). The boxes highlight the user's selections at each of the three levels. A video of the software in action is available to view on YouTube (14).

Experiment 1

Similar to many UK medical schools, the University of Edinburgh's undergraduate dermatology teaching programme consists of an introductory series of 8 lectures, followed by a two-week clinical attachment incorporating 9 demonstration clinics (15, 16). All students who attended for their two-week clinical attachment over a three-month period (November 2009 to January 2010) were recruited into the study. In total, 60 students were enrolled (4 batches of between 14 and 16 students). Other than 8 introductory lectures (one of which was dedicated to skin cancer) none of the students had prior clinical experience of dermatology. Thirty-six (60%) of the students were female.

On the morning of Day 1 of the dermatology attachment (prior to seeing any patients), each batch of students was randomly split into two groups; the first group (the "software" group; $n=31$) was asked to identify each of the 12 index images using the software and the second group (the "control" group; $n=29$) was asked to identify the 12 test images by writing their diagnosis on an answer sheet. Test instructions were standardized across the batches of students. We were "generous", in what we accepted as correct answers for the control group, allowing spelling mistakes, incomplete terminology, abbreviations and lay terms. After the Day 1 test no score or feedback was provided to either group. Exactly the same experiment was repeated on the afternoon of Day 10 at the end of the students' dermatology attachment. The format of both the Day 1 and Day 10 experiments was

identical, except that the introductory software video was not repeated to the software group on Day 10.

The 12 test images were presented to both groups of subjects in the same order and in an identical format. For both the software and control groups the skin lesion images were displayed using the same Apple iMac G5 20" monitors (Apple, CA, USA) with identical resolutions (1650 × 1050), calibrated for colour inconsistencies using the Pantone Huey Pro calibration (Pantone LLC, NJ, USA). The experiments were all undertaken in a designated curtained room with similar ambient lighting conditions. No time restrictions were imposed for either group. Constructive feedback was only given after each batch of students had completed the Day 10 test during an additional tutorial.

Experiment 2

Twenty lay members of the public were recruited between May and July 2010. Mean age was 33 years (age range 21–61 years). Seventy-five percent of the subjects were female. All but 4 had completed university education and the 20 subjects were employed in a wide range of different occupations (e.g. solicitor, accountant, teacher, secretary, chef). No volunteer had any personal experience of skin cancer nor had undergone any tuition in the identification of skin lesions.

The 20 subjects were provided with the same introductory video guide to the software as the students, but no additional training. The experimental set-up was identical to that undertaken by the students, with the same 12 test images and an identical version of the software (as described above). This group of subjects will subsequently be referred to as the "lay" group.

Statistical analysis of all results was undertaken using R for Mac OS, V2.9.0 (17).

Ethics

The NHS Lothian research ethics committee granted permission for the collection and use of the images. Additional permission for the use of medical students in this research was granted through the University's "Committee for the use of medical student volunteers".

RESULTS

Experiment 1

Ninety-three percent (112/120) of students completed both the Day 1 and Day 10 tests. Student absence was distributed evenly across the 4 test groups; Day 1 control group ($n=1$), Day 10 control group ($n=3$), Day 1 software group ($n=1$), and Day 10 software group ($n=3$).

At the start of their dermatology attachment (Day 1 test), out of the 12 test images, the control group correctly diagnosed a median of one image with a diagnostic accuracy of 16% (55/336), in the same Day 1 test the software group correctly identified a median of 12 images, resulting in a diagnostic accuracy of 99% (357/360). At the end of the students' dermatology attachment (Day 10 test) the control group correctly diagnosed a median of 6 images with a diagnostic accuracy of 51% (160/312) and the software group matched 12 images correctly, with a diagnostic accuracy of 99% (335/336). Results are shown in Fig. 2.

Two-sample Wilcoxon tests showed that the scores at Day 1 between the software and control group were significantly different ($p<0.0001$), as were the two groups scores at the end of the students' attachment on Day 10 ($p<0.0001$). Wilcoxon match-pairs test showed that the control group's scores improved significantly ($p<0.0001$) over their attachment, whereas the software groups score did not appear to change ($p=0.582$).

There was no difference in test scores between the four batches of students or between the sexes. In addition, we saw no particular pattern of results with respect to lesion type.

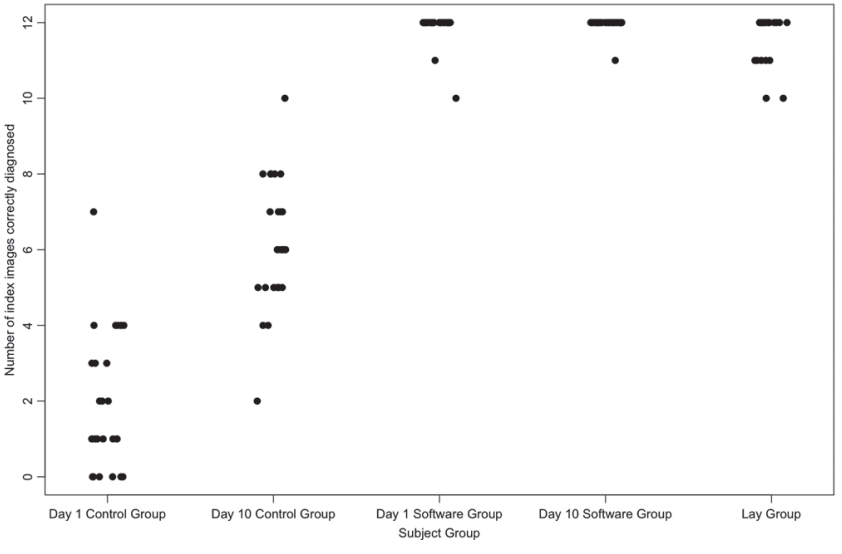

Fig. 2. Plot of all 60 students' scores by group and test date, and the 20 lay novices' scores. The maximum score of 12 is achieved by correctly identifying all the test images. Day 1 control group ($n=28$, median score 1), Day 10 control group ($n=26$, median score 6), Day 1 software group ($n=30$, median score 12), Day 10 software group ($n=28$, median score 12). Lay group score ($n=20$, median score 12).

Experiment 2

The lay group, using the software, correctly identified a median of 12 images resulting in a diagnostic accuracy of 96% (231/240) (see Fig. 2). Again, there was no difference in test scores between the sexes or with respect to lesion type.

Two-sample Wilcoxon tests showed that the student control group had significantly inferior diagnostic accuracy compared with the lay group, at both the start and end of their dermatology attachment ($p<0.0001$).

DISCUSSION

Our results show clearly, within the constraints of a limited range of diagnostic possibilities and an image-based approach, that medical students

are able to utilize visual matching as a diagnostic strategy and achieve diagnostic scores that are higher than medical students who have completed a standard clinical dermatological attachment. This ability is not confined to medical students; as we subsequently went on to examine a group of non-medical trained individuals who scored similarly. This success was therefore achieved by test subjects making matches on the basis of visual similarity without any attempt to apply any explicit rules of likeness based on dermatological knowledge. We believe that these results are in keeping with the idea that promotion of non-analytical-based reasoning strategies may be useful educationally useful for non-experts (18). There are, however, a number of limitations to our work and points worthy of further elaboration.

Immediately after completing their undergraduate dermatology teaching attachment, students' unaided diagnostic accuracy for common skin lesions was only 51%. Although it is mildly reassuring that the students improved their diagnostic acumen over the course of their two-week attachment, a final diagnostic accuracy of 51% is perhaps poor, although obviously any absolute score is dependent on the difficulty of the test set. This result is more sobering when one considers that the level of these students' diagnostic accuracy may reflect an artificially raised result; the students' achieved this level of accuracy after double-exposure to the 12 test images (the students had previously viewed, albeit without feedback, the 12 images during the first test on Day 1 of the attachment). In addition, as with the majority of UK undergraduate dermatological attachments, our students were in their penultimate clinical year, so it is probable that by the time they graduate a further drop off in their diagnostic performance could be expected. However disappointing the students' scores may seem, they are, in fact, not dissimilar to previous studies that have investigated the diagnostic accuracy of non-dermatologists after medical school training with colour images (19, 20).

Our results are also constrained by other features of our study design. For obvious practical reasons, our testing relied on matching to an image rather than to a lesion on a real patient. There is still some uncertainty about the limitations of virtual vs. real patients in this context, although we note that images are widely used in teaching and examination of clinical competence, and that if we think of our approach as a teaching tool for clinicians then virtual patients may be thought to at least supplement patient exposure. If such a matching tool is envisioned as a diagnostic support tool for the lay public (for instance, in encouraging early presentation of suspicious pigmented lesions) then this limitation needs further exploration.

In the present studies we did not attempt to represent the whole of the complexity of dermatological morphology, focusing rather on a range of common lesions. Any performance figures clearly must, in a fundamental way, relate to the difficulty or atypicality of the test set. However, we would argue that our approach was that of proof-of-concept, which, given the results, suggests further work is merited. The approach we have used based on only 80 images is, however, eminently scalable, and we are currently building software that will allow examination of several hundred images. Our view is that as the database increases in size it may become increasingly powerful, assuming that we can order it in a way that is intuitive to the user. This can either be based on ordering of images based on automatically extracted properties ("computer vision"), or user feedback, or some combination of the two (21–25).

That novices were able to identify skin lesions without any explicit definition of likeness or specific rule-based analysis (such as the ABCD) makes our approach fundamentally different from most previous strategies to improve non-expert diagnosis. Whilst it is tempting to want to explore exactly what features of images users are actually matching to, this may be neither necessary or tractable. Ironically despite its appeal, in many situations there is clear evidence that exclusive rule-based strategies may in fact diminish diagnostic accuracy or decrease the utility of decision-making (10, 18, 26–28).

Finally, whatever the insights our work provides into the relative different diagnostic strategies, we can envision two applications of our approach. The first would be as a teaching and learning tool for clinicians. Whilst we have not demonstrated that any learning took place in our experiments, merely that we provided subjects with a software tool that enabled them to achieve something they would not have been able to achieve without the software, it is not difficult to imagine how such a system might be embedded with teaching material for clinicians. The second application is for the lay public, and the approach we describe might be considered an extension of the posters and leaflets that are used to educate the public about the warnings signs of skin cancer. Although many will be anxious about whether such approaches are safe, we note that 80% of internet users have already undertaken health-related searches (29) and that there is some evidence that current strategies may in fact worsen rather than improve diagnostic performance (18). It is surely better to examine experimentally how such approaches might improve matters rather than make unwarranted assumptions about how humans are able to categorize skin lesions.

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