Using artificial intelligence to improve wound image quality: a feasibility study

KEY WORDS
- Artificial intelligence
- Blurred images
- Surgical site infection
- Wound care

Background: Artificial intelligence or AI has been used successfully in wound measurement and diagnosis. We undertook a feasibility study to improve image quality for wounds healing by primary intention. **Method:** Within our AI Lab, we used a three-step approach. Firstly, we collected a test set (and training set) of clear and blurred images and reviewed existing solutions, models and documentation. In the next stage, a model was trained to be able to automatically classify between the two groups. We used a non-wound publicly available data set of blurred and clear images, looking specifically at contours in the images to focus into blur. Finally, the model was tested on a set of wound images, which had been pre-classified by surveillance colleagues (266 images total). **Result:** We were able set a threshold value on the resulting algorithm, which resulted in a 5% false rejection of good images, while correctly flagging 62% of the images classified as blurred by surveillance colleagues. This operating point was selected for further investigation and user acceptability testing. **Conclusion:** Clinical wound care and quality improvement using visual data requires high-quality images.

Similar to other cardiac centres, Harefield hospital nursing staff routinely take photos of surgical wounds for Photo at Discharge (PaD) (Rochon et al, 2020; Cardiothoracic Interdisciplinary Research Network, 2020). The key aims of PaD are to improve the information about the surgical wound for the patient, carers and healthcare providers; increase patient confidence for self-management, and provide a practical tool for monitoring the wound, including early detection of any concerns (Rochon et al, 2016). Visual data is a vital component of clinical decision-making and in the context of COVID-19 has become more important than ever. PaD relies on a high-quality surgical wound image, which is sharp, clear and well-formatted (centred, at an appropriate angle), free of distracting details or objects and with plain background. To standardise the quality of images, a comprehensive programme was introduced for all ward staff involved (Table 1).

Despite this framework, approximately 1% of images were of suboptimal quality (Rochon et al, 2017). In relation to PaD, low-quality images may have an impact at three points in this pathway. Firstly, the team review PaD routinely. Without a high-quality image at this point, important details of the wound's appearance at the time of discharge from hospital may be lacking, such the presence of any wound closure material (Table 2). In addition, patients are less able to make objective comparisons between the state of their wound over time if the image of their surgical wound isn't clear. Finally, in the case of wound reviews or readmission for wound care, comparison between existing images and current wound state becomes difficult.

To understand the problem more fully, a review was conducted on a sample of images deemed to be low-quality. The results suggested shadows and lighting, formatting and blur where the most common concerns. However, blur had the biggest impact on the use of the image. For instance, in relation to the previous example of wound closure material, blur can prevent the reviewer from identifying the presence of a suture knot or determining if the surgical clips were placed over the approximated wound edges in an equidistant fashion.

Blur may be the result of the subject moving but

MELISSA ROCHON
Quality & Safety Lead for Surveillance, Royal Brompton & Harefield NHS Foundation Trust (RBHT)

JAMES JURKIEWICZ
Chief Technical Officer, Islacare Ltd

CARLOS MORAIS
Clinical Nurse Specialist in Surveillance, RBHT

TARIRO GONDO
Clinical Nurse Specialist in Surveillance, RBHT

Table 1. Framework for ensuring high-quality digital images for wounds	
Activities for ensuring high-quality images	Tools/Resources
Baseline and ongoing assessment of training needs, resources	Quality improvement methodology: see Rochon et al, 2016 Long Term Success Tool: see Rochon et al, 2020 Staff feedback and audit: see Dobbs and Thompson, 2018 Appropriate equipment provided and maintained by the workplace
Face-to-face training (1-2-1)	Step-by-step guide Competency framework
Free online e-course Using Digital Images in Wound Care	Register at www.3mlearning.co.uk with access code PAD2020
Incentives	Monthly prize draws to win a £25 Amazon voucher (to qualify for the prize draw, PaD image had to include the entire incision, correctly angled, appropriate size and without shadow). Evidence of benefits: see Rochon and Morais, 2019
Regular audits of wound images and feedback	Run charts, control charts Feedback to individual staff member
Standard operating procedure (SOP) and Information Governance Policy	Local For a national resource, register with the National Wound Care Strategy Programme Data & Informatics enabler stream for key stakeholder consultation on recommendations for the use of digital images in wound care https://www.ahsnnetwork.com/about-academic-health-science-networks/national-programmes-priorities/national-wound-care-strategy-programme/national-wound-care-strategy-programme-board/enabler-workstreams/data-and-information-enabler-workstream

for PaD this was more commonly caused by the movement of camera or device by the staff member. To avoid this, staff were advised to keep the device still and avoid talking while taking the picture. As training had not reduced the incidence of blur, and due to the impact on the utility of the image, blur reduction was selected for a project using artificial intelligence (see *Box 1*).

AI Lab Project: 'Blur detection'

A collaborative agreement was signed by the Trust and Islacare Ltd (Isla) an industry partner specialising in visual data. The project was undertaken in Trust AI Lab in July 2020.

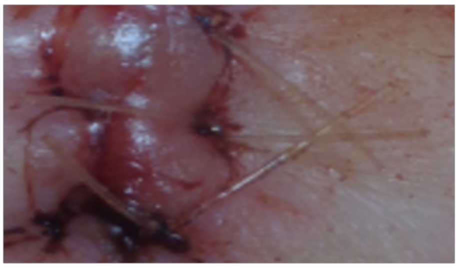
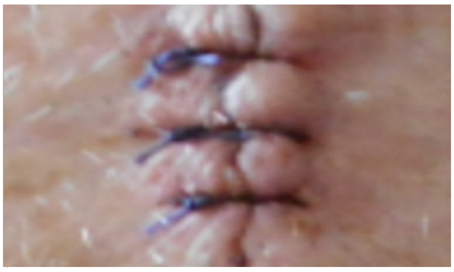
METHODS

The feasibility study was implemented in three distinct steps:

- **Review data:** As part of the collaboration between the Trust and Isla, the Trust shared a set of acceptable and unacceptable images with respect to blur. These were reviewed by the software Engineering team at Isla to identify suitable approaches for automated segmentation between the acceptable and unacceptable images
- **Test existing methods:** Isla used existing

Box 1. Description of concepts used in AI Lab

Artificial intelligence or AI: a term which can be applied to any machine that exhibits traits associated with a human mind, such as learning and problem-solving.
Machine Learning: a subset of AI, in which computer algorithms are 'trained' with sets of data to behave a certain way. Once a machine learning model has been trained appropriately, it can apply this learning on to new examples outside the training data. Training can be 'supervised', i.e programmers specify what the training should be focussed on using structured and labelled training data, or 'unsupervised', when unlabelled and unstructured data can be given to the machine, which will 'learn' which patterns to look for.
Deep learning: is another term for 'unsupervised' learning described above.
Computer vision: describes the ability for a computer to interpret an image, in a similar way to the human eye and brain, to be able to, for example, recognise a bus in an image.

Table 2. Wound closure materials		
Absorbable sutures		Usually clear or brownish, plastic-like appearance Do not trim or remove. Allow to absorb over time Watch for 'reinforced' dissolvable sutures at bottom of the wound
Non-absorbable sutures		Dark, thread-like appearance Common for drains, surgical wound dehiscence, sutures under strain 10–14 days (check with team)
Deep tension sutures		Commonly used for wound revision 3 weeks ± drain The tubing is a protective strategy to prevent the sutures from cutting into the skin or leaving a permanent imprint as these sutures are usually left for longer periods
Tissue glue adhesive		Glue /tissue adhesive, e.g. Dermabond Can be used with a dressing Allow adhesive to slough naturally (usually in 5–10 days), there should be only transient wetting of the site (not be scrubbed, soaked, or exposed to prolonged wetness)
Wound closure tapes		Wound closure tapes (e.g. Steri-Strips) are composed of strips of reinforced microporous surgical adhesive tape. Used to provide extra support to a suture line, either when running subcuticular sutures or after sutures are removed. Keep dry. Minimum 5–7 days, allow to curl up before gentle soak removal
Surgical staples (clips)		Left *in situ* 10–14 days. Longer = skin can start to react Consider removing alternate clips as necessary

blur detection methods (Laplacian, Blind/ Referenceless Image Spatial Quality Evaluator (BRISQUE), etc.) to obtain initial quality scores for the test set

- **Refine promising methods:** reviewing false positives and negatives, the Isla team made tweaks to the implementation (i.e pre-cropping, operating point changes, etc.) to identify improvements in performance and achieve a promising accuracy for this initial study.

The team decided to use existing publicly available datasets for the training of a machine learning model, so that the model could be tested on the set of images provided by the Trust. The model would return a 'blurriness' score for each image, so that the project team could set a threshold where any results above a certain score would trigger an alert to the user, offering them to retake the image. At any threshold score decided, we could calculate from the test set (taking a positive result as being blurry):

- False positive rate: i.e of all the clear images, what percentage returned a 'blurred' classification?
- False negative rate: i.e of all the blurred images, what percentage returned a 'clear' classification?

Acknowledging that the majority of submitted images were in fact suitably clear, the project team opted to limit the false positive rate to a predetermined point of 5%, meaning that only 5% of users submitting a clear image would be interrupted and requested to capture a new image.

RESULTS

See *Table 3*, which indicates rejection rates at different thresholds points. We see that, as the threshold point is increased, the number of rejections for both classes increases. However, since we expect blurred images to return lower scores, we see the rates of rejection for blurred images rise far higher than for clear images. Note: an untrained model would not discriminate between the two classes, and we would see the same rates of rejection at each interval. Following an initial study to test the feasibility of the approach, the project team set the threshold to comply with the 5% false positive constraint and observed a false negative rate of 38%, i.e 62% of blurred images were flagged. On further review with the project team, it was agreed that a proportion of the 5% should in fact have been classed as blurry in the first place, bringing the false positive rate down to 3%. These results indicate that if users comply with the alerts, then the total blurred images received could drop from 5% down to less than 2% (*Figure 1*). It was decided that the solution should be implemented into the platform to monitor the 'real world' impact, to gather more information ahead of making further refinements to the algorithm.

DISCUSSION

In UK research studies using digital images for SSI surveillance, approximately 1–2% of images submissions are excluded due to image quality issues (Cardiac SSI Network, 2020). In our 'real world' setting, the risk of poor-quality images was similar.

We decided to focus on blur detection as it was relevant for our patient group with wounds healing by primary intention, with broader relevance to all wound images. A 2020 systematic review examined AI computational methodologies for wound measurement and dimensions (size, shape, location, trace, area, volume wound length, depths, volume, surface area, surface curvature, and colours) and diagnosis (binary, classification,

Table 3. Rejection rates at varying algorithm operating thresholds

Operating point with rejections below this point	Clear images rejected(%)	Blurred images rejected (%)
0	0%	0%
5	0%	35%
10	5%	62%
12.5	8%	69%
15	12%	73%
20	18%	81%
25	23%	85%

Figure 1. Pictorial representation of rejection rates at varying algorithm operating thresholds. Setting the operating threshold at a score of 10 allows us to identify >60% of the 'most blurry' images, while only incorrectly flagging 5% 'clear' images.

tissue types) including 2D and 3D images and text (Anisuzzaman et al, 2020). A potential area of interest for us would include SSI diagnosis, but we note concerns over the lack of formal assessment and regulation of the technology (Morley et al, 2020) and thus decided to focus on image quality. For our acute setting, surgical wound closure and incisional assessment may highlight potential risk of SSI. Blencowe et al reported 38 domains or factors which may influence the quality of wound closure. The authors suggested that excess suture material, gaping or opening and issues with tension may increase the risk of SSI (Blencowe et al, 2019). In our experience, these details may not be captured in medical or nurses' notes but might be evident in high-quality wound pictures; however, they would not be detectable if the image was blurred.

We believe that computer vision and machine learning have a huge part to play in the future of healthcare and the opportunities just within the scope of wound surveillance are very exciting. However, the reality is that high performance in machine learning can only be achieved with high-quality training data. As a result, this application of quality screening solves an immediate problem ensuring timely clinical decision-making and good patient experience, and also paves the way for further development and learning. We selected an AI approach as relying on image resolution (the number of pixels) or the size of the image file would result in high rates of incorrect flagging. Our method means that the image quality is reviewed seamlessly and as a result the user is informed of an issue so that they can retake a picture if needed.

User experience, for staff and patients/carers, was an important consideration to our project group. Any requirements to retake an image due to blur would need to be almost instantaneous to ensure the user could retake while still within the capture flow. If we are able to automatically detect that an image is blurred, we would be able to give a prompt to the user and ask them to retake. This has two benefits: the user is informed immediately what the issue is and can rectify with context and there is no need for manual review/follow up. In practice, to benefit from blur detection, encrypted mobile devices (such as a smartphone or tablet) should be used. Images

Acknowledgments

The authors would like to thank Dr Lorenz Berger, Dr Eoin Hyde, Clare Reed, Mr Sunil Bhudia, Michael White and the staff, patients and carers at RBHT.

uploaded to the Isla platform by a digital camera still flag the image as blurred; however, the opportunity to retake the image may have passed. With a mobile device, the algorithm for blur detection runs in the background. After approximately three seconds, if blur is detected, a user prompt appears, 'Blur detected in image. We suggest you take a new picture.' The user has the option to submit the original picture or to proceed to take a new picture.

Limitation and future work

Using an automated approach always carries some risk: for instance, it may be that blur is detected in the background of an otherwise perfect image, or a high-quality image may be flagged incorrectly. Another limitation is the relatively small sample size of wound images (*n*=266) that was used. Our next steps are to further develop the model on a larger dataset for increased accuracy of segmentation and iterate on implementation design from user and patient feedback.

CONCLUSION

AI opens up opportunities for improved accuracy, efficiency and consistency in care and management for higher-quality patient care. Following an audit of images to determine key issues for images used for PaD, we decided to focus on reducing the risk of image blur. To do this, we collected a test set (and training set) of clear and blurred images. With Isla, we tested a number of different detection techniques and undertook initial refinements. After reviewing different threshold results, we were ready to implement the detection method in practice, gain user feedback and continue the iterative journey to improve wound image quality. WUK

REFERENCES

Anisuzzaman DM, Wang C, Rostami B et al (2020) Image based artificial intelligence in wound assessment: a systematic review https://ui.adsabs.harvard.edu/abs/2020arXiv200907141A (accessed 28 October 2020)

Blencowe N, Rooshenas L, Tolkien, Z et al (2019) A qualitative study to identify indicators of the quality of wound closure. *Journal of Infection Prevention* 20(5):214-223. https://doi.org/10.1177%2F1757177419846280

CARDIAC SSI Network (2020) The use of digital images in surgical site infection surveillance. YouTube. https://www.youtube.com/watch?v=gxrnb8cSSP4&feature=youtu.be. (accessed 28 October 2020)

Cardiothoracic Interdisciplinary Research Network, National Cardiac Benchmarking Collaborative, Public Health England. National Survey of Variations in Practice (ViP) in the Prevention of Surgical Site Infections in Cardiac Surgery, United Kingdom & Ireland. *Journal of Hospital Infection Prevention* [In press] https://doi.org/10.1016/j.jhin.2020.09.016

Dobbs S, Thompson A (2018) Reducing the burden and stress of SSI. Clinical Services Journal, 31-34.

Morley J, Floridi L, Goldacre B (2020) The poor performance of apps assessing skin cancer risk. *BMJ* 368: m428. https://doi.org/10.1136/bmj.m428

Rochon M, Morais C (2019) Five years on: a national patient and public involvement audit and economic assessment of photo at discharge. *Wounds UK* 15(3):28–35

Rochon M, Magboo R, Barlow C et al (2020) Implementation of enhanced patient education for surgical site infection (SSI) prevention in cardiac surgery: survey findings from three english hospitals. *Br J Nursing* 29(17):994-1002. https://doi.org/10.12968/bjon.2020.29.17.994

Rochon M, Makecha S, Morais C et al (2016) Quality improvement approach to reducing readmission for surgical site infection. *Wounds UK* 12(2):26–31

Rochon M, Sanders, Gallagher R (2017) Service design: a database approach to the management of wounds in the hospital setting. *Wounds UK* 13(4):41–49