Machine Learning for Melanoma Management in a Clinical Setting

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Abstract. This paper describes work in progress on a melanoma management platform known as Simplicity MDT, which is in use in major hospitals for the collection, management and analysis of clinical data. It includes a facility for uploading and managing high resolution digital colour photographs of melanoma lesions. As the data managed by this platform is structured and annotated, it is proposed that this could serve as a basis for supervised training datasets for machine learning. Machine learning models trained using this data can serve the wider community for screening, diagnostic and prognostic purposes. The proposed machine learning architecture includes integration with a model zoo, which provides networks that are pre-trained on publicly available datasets. An overview of the current system is presented and a roadmap for future developments is outlined.

Keywords: Machine Learning, Melanoma, Connected Health.

1 Introduction

The motivation for the development of a machine learning driven melanoma management platform stems from engagement with clinical end users, doctors, oncologists and other clinical specialists who are searching for innovative solutions to impact the treatment of melanoma. Melanoma is a malignant tumour of melanocytes with about 160,000 new cases diagnosed annually, with high prevalence among Europeans. This is a serious health issue and the aim of this research is to impact the diagnosis of this disease by the proposed integration of machine vision-based classification, through deep learning technology, with the myriad of information sources in electronic health records captured through multi-disciplinary team discussions.

Multidisciplinary care is currently accepted as best practice in the delivery of high-quality cancer management in Ireland and internationally. Multidisciplinary Team Meetings (MDTMs) take place at regular intervals, where a team comprised of medical experts across different relevant disciplines come together to discuss patient cases, review treatment, and plan treatments [1]. Care delivered to patients through a multidisciplinary approach results in positive outcomes especially in terms of diagnosis and treatment planning, patient satisfaction and improved survival rates. Participating in

MDTM's also has positive outcomes for clinicians – centred around the opportunity for education, improved communication and working relationships. While MDTMs enhance healthcare, they are mostly reliant on antiquated paper-based systems and integrated software management tools that are sorely lacking. Moreover, there is a lost opportunity for allowing patients to participate in the care pathway. The melanoma management platform Simplicity MDT provides significant opportunity for gathering clinically labelled digital images of melanoma lesions (see screenshot of system in Figure 1). The system has already managed over 8,000 cancer cases, including over 1,000 melanoma cases with digital imaging. This rich data set provides a basis for machine-based assessment by allowing health professionals to gather valuable supervised training data that can be used to augment existing deep learning models to enhance clinical assessment.

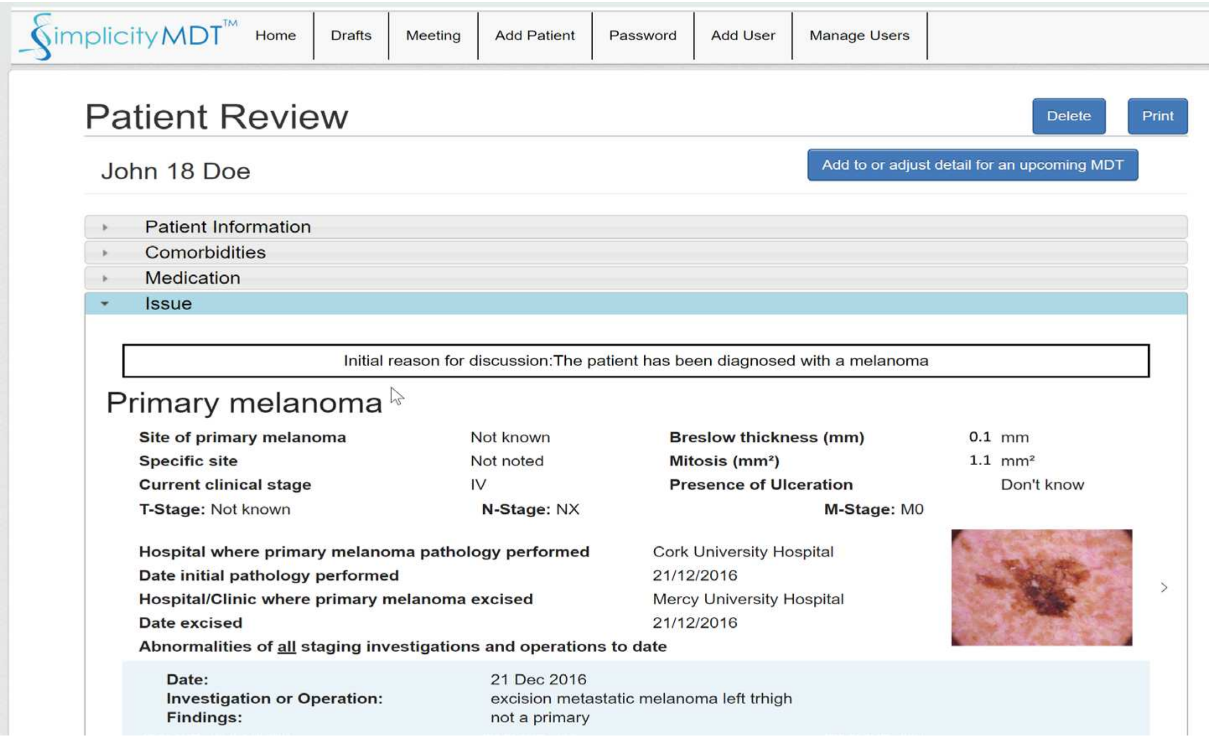

Fig. 1. Screenshot of Simplicity MDT with clinically labeled images.

2 Machine Learning for Melanoma Applications

The term machine learning is used to refer to the field of computer science concerned with developing algorithms that can mine datasets to build statistical models [2]. Machine learning systems rely on training data that can either be labelled or unlabelled [3]. Labelled data allows researchers to apply "supervised" learning algorithms, which can progressively train models to find associations between input patterns and their expected labels [4]. Labelling data can be extremely expensive and time consuming, so any framework that facilitates the collection and labelling of data can serve as a useful basis for building supervised machine learning models [5]. Unsupervised machine learning models on the other hand do not require labelled data, but in turn can't be used to generalize label mappings for new data, instead finding use in more niche applications, such as anomaly detection.

Deep neural networks are a class of ML model that come in a variety of architectures, but all are characterized as having a large number of layers, which are used to detect low-level features and map these two increasingly complex models in the higher layers of the network architecture [6]. Deep neural networks have had significant impact on the classification of skin cancer as outlined in the Nature publication from Estava *et al.* [7], where they note that automated classification of skin lesions using images is a challenging task owing to the fine-grained variability in the appearance of skin lesions. A class of deep learning networks, known as convolutional neural networks (CNNs), have demonstrated impact in challenging visual classification tasks in a variety of domains [8] [9] [10] [11] [12] [13]. Estava *et al.* developed a CNN for the classification of skin lesions using digital images, using only raw pixels and disease labels as inputs and tested its performance against 21 qualified dermatologists on clinically assessed images with the following binary classification use cases:

- Keratinocyte carcinomas (the most common skin cancer) versus benign seborrheic keratoses.
- Malignant melanomas (the most fatal skin cancer) versus benign nevi.

Their system performed as well as the experts across both tasks, indicating that machine learning can achieve a level of accuracy comparable to a dermatologist for skin cancer classification. Estava *et al.* proposed that deep neural networks deployed to devices such as smart phones, could bring important dermatology assessment to a wider audience and can possibly deliver universal access to diagnostic care.

We plan to take up this challenge, by designing an integrated cloud based mobile solution that can enhance automated skin cancer classification by leveraging mobile edge computing (MEC), which provides cloud computing capabilities at the edge of the network [14] and optimises performance by bringing computing resources to the data. Furthermore, recent advances in edge computing will have profound impacts on healthcare systems [15] [16].

Connected healthcare has already been enhanced with the proliferation of technologies [17] and mobile hardware is having a positive impact on healthcare, e.g. the monitoring of hypertensive patients with connected blood pressure monitors. Similarly, there have been a number of smart-phone apps developed for the detection of melanoma [18] and while they provide an array of features including information, education, classification, risk assessment and change monitoring, they can only provide limited processing power due to the current processing limitations of mobile devices.

Smart mobile networks offer increased processing through mobile edge computing, which offers low latency, high bandwidth and localized cloud computing capabilities [19]. A major benefit of 5G technology is the provision of *ad hoc* local cloud instances via a mobile network [20], which allows participating institutions to "*securely share patient genomic, imaging and clinical data for potentially lifesaving discoveries. It will enable large amounts of data from sites all around the world to be analyzed in a distributed way, while preserving the privacy and security of patient data at each site*" [21].

3 Future Work

We aim to develop Simplicity MDT as a system for gathering high quality clinically labelled digital images and integrate this system with the advances in both mobile edge computing and deep learning to provide universal platform for assessing suspect skin cancer lesions. The system will have the following features:

- Use of state-of-the-art pre-trained melanoma machine learning models, based on evaluations of results using ImageNet, VGG19, ResNet-50 [22], Inception [11] and newer architectures, including PolyNet [23], ResNeXt [24], Densenet [25], SENets [26] and DualPathNet [27] [22].
- Machine learning implemented via mobile edge technology in a secure and federated environment [28]. The use of mobile edge local cloud computing will allow clinicians in distributed locations, to securely review, edit and discuss cancer cases in real time within multi-disciplinary teams.
- Ongoing experts "human-in-the-loop" to constantly label, validate and update models [29] [30]. Our Simplicity MDT software platform serves as a basis for collecting numerous multivariate labels which can be used to help build prediction and classification models for melanoma images and other datasets.

In addition, a vast range of techniques can be used to enhance classification and object detection. Having a network of partners, collaborators and consumers can provide a wealth of access to resources for creating quality labeled data sets.

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