

Odin’s Eye – A Close Look at Gamification of Labelling of Ophthalmic Diseases

Fuxin Fan¹, Jingna Qiu¹, JiaWei Wang¹, Stelica Valianos¹, Muhammad Muqtasid Farooq¹, Weilin Fu¹, Florian Kordon^{1,2}, and Andreas Maier^{1,2,3}

¹ Pattern Recognition Lab, Friedrich-Alexander-Universität Erlangen-Nürnberg (FAU), Erlangen, Germany

² Erlangen Graduate School in Advanced Optical Technologies (SAOT), Friedrich-Alexander-Universität Erlangen-Nürnberg (FAU), Erlangen, Germany

³ Machine Intelligence, Friedrich-Alexander-Universität Erlangen-Nürnberg (FAU), Erlangen, Germany
andreas.maier@fau.de

Introduction

State of the art deep learning [1] requires vast amounts of accurately labelled training data to enable high classification performance [2]. In order to obtain sufficient amounts of data, data donation is a feasible approach [3]. Yet, the data is only useable, if correct annotations are present. One way to create such annotations is crowdsourcing via gamification. In this paper, we present an integrated training and annotation approach that allows large scale annotation of ophthalmic diseases.

Methods

We created a game called “Odin’s Eye” in order to make image classification an exciting and rewarding experience. The game has three modes that are used to slowly lead the player to the complex field of ophthalmic diseases. In order to do so, we used image data from the ODIR 2019 Challenge (<https://odir2019.grand-challenge.org/dataset/>). The dataset contains more than 7000 images showing healthy eye data and different pathologies.

In “Normal Mode” the player is shown one fundus image and is asked to select whether the shown image is “normal” or shows Cataract, Macular Degeneration, Glaucoma, Retinopathy, or Myopia (**Fig. 1**). After a sufficient number of correct answers, the player can access the unlabeled mode, in which the user is able to collect points for labelling images that are of unknown classification.

The “Difficult Mode” is inspired by puzzle games such as Candy Crush or Zookeeper (**Fig. 2**). Here, the player is displayed various fundus images and is asked to align them such that three images showing the same pathology form either a row or a column. Once such a triplet is found, it disappears and new images enter the game canvas from the top. In order to make the game more challenging, a curtain enters the field of view from the top that gradually increases the pressure on the player. After

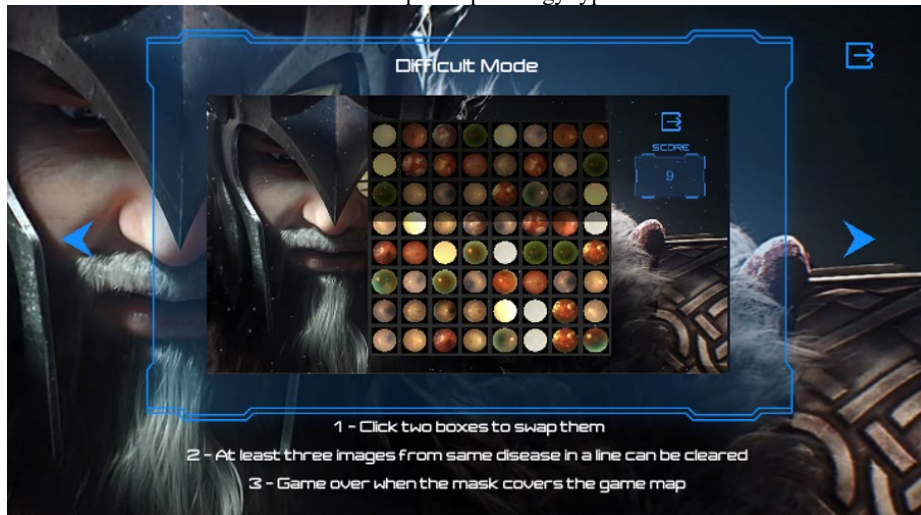
finding five triplets, the curtain is raised a little and the time limit is increased. The ideas of using triplets is appealing as images of unknown pathology can be mixed into the game area. The player will implicitly classify such images when he tries to align them with two more images of the same class.

A leader board shows high scores in order to encourage players to compare their scores online and to compete in creating a large number of annotations.

Fig. 1. Visualization of the classification task in the “Normal Mode”.



Fig. 2. Illustration of the “Difficult Mode” where the player has to align fundus images based on the depicted pathology type.



Results

A prototype was implemented in Unity3D [4]. In order to test the game idea, only five prototypic images were chosen for each pathology at present. The difficulty of the game can easily be increased by increasing this number. First experiences with test players confirmed that in particular the “Difficult Mode” has a very rewarding game experience. Prototypes are available as Android APK and WebGL (<https://www.medicaldatadonors.org/index.php/odins-eye/>). An in-game video was created to demonstrate the gameplay (<https://youtu.be/UehnND9gkvY>).

Conclusion

We believe that we created a challenging yet rewarding game experience. In future versions, we will make use of additional images from the ODIR 2019 dataset in order to create slowly increasing difficulty in the game to convince even expert players to keep playing Odin’s Eye.

References

1. Maier, A., Syben, C., Lasser, T., & Riess, C. (2019). A gentle introduction to deep learning in medical image processing. *Zeitschrift für Medizinische Physik*, 29(2), 86-101.
2. Bertram, C. A., Aubreville, M., Marzahl, C., Maier, A., & Klopffleisch, R. (2019). A large-scale dataset for mitotic figure assessment on whole slide images of canine cutaneous mast cell tumor. *Scientific data*, 6(1), 1-9.
3. Servadei, L., Schmidt, R., Eidelloth, C., & Maier, A. (2017, October). Medical Monkeys: A Crowdsourcing Approach to Medical Big Data. In *OTM Confederated International Conferences "On the Move to Meaningful Internet Systems"* (pp. 87-97). Springer, Cham.
4. Murray, J. W. (2014). *C# game programming cookbook for Unity 3D*. AK Peters/CRC Press.