Tactiled: Towards More and Better Tactile Graphics Using Machine Learning

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ABSTRACT

Tactile graphics (TG) can help people with visual disabilities access visual concepts. However, the number of TGs available to users is considerably limited because they need to be created by designers and teachers of the visually impaired (TVIs) with extensive experience. High-quality images can be transformed into TGs. In order to increase the availability of TGs, we trained a machine learning (ML) model that identifies suitable and unsuitable images for TG transformation (See Figure 1). This model would help users identify high-quality images that can be transformed into TGs. The poster presents (1) the ML model trained with 800 images collected from the American Printing House tactile Library and the researchers, (2) a web application that lets TVIs retrain the model by feeding new images and helping with the classification. This system can then be used by anyone, especially parents and teachers, as a filter to produce new TGs.

Author Keywords

Tactile Graphics; Machine Learning; Teachers of the visually impaired.

ACM Classification Keywords

• **Human-centered computing~Accessibility systems and tools**

INTRODUCTION

Tactile graphics are important alternative tools to represent visual content to people with visual impairments [3]. Recent advancements [2][6][7] in producing TGs should have greatly increased the availability of them, but this has not been the case. The impact of the low availability of TGs can be seen in recent surveys, in which 9-19 year old blind students in the United States and Canada reported: 55% encountered only up to 8 TGs or less in a monthly basis [11].

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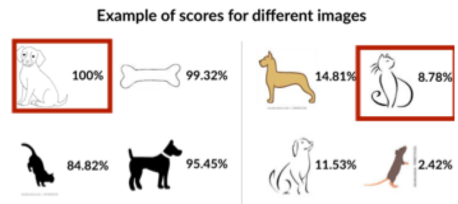

Figure 1. Results for different images tested with Tactiled. On the left side we have images determined as suitable by our TVI input and the ml model trained. On the right side we have random images that are categorized as unsuitable images to make TGs because of their complexity.

In prior work, researchers invented algorithms to increase the availability of TGs [1][9][10]. They applied image processing algorithms to transform a source image into a TG. However, the issue with this approach is that there is no way of validating the effectiveness of the output without relying on a TG expert. TGs lack accuracy when the source image is too complex [5]. Students may struggle to understand differences with the texture and the actual content. That is why there is a need for an automated tool that evaluates and suggests a source image that is more suitable for the use of TGs.

To validate images in a more efficient manner and provide more TGs, we present Tactiled. Tactiled is a web-platform that consists of (1) images that are transformable to TGs and (2) an online learning model, where users can identify if an image is transformable to a TG and TVIs can retrain the model. The classification model uses the TVIs feedback to increase the effectiveness of classification.

In this poster, we describe two components: the ML model and the web platform. We implemented the identification, search and retraining functionalities in a web-platform (as seen in Figure 2-4) and trained a ML model with Firebase [8] and Google cloud platform services. Our tool classifies images as good candidates to be translated to TGs and suggests images that are good candidates to be translated to TGs using our accumulated knowledge (model) and data.

THE MODEL

The goal of this model is to classify images into two categories: TG transformable and not TG transformable. The probability given by the model is shown as a score from 0 to 100, 0 being unsuitable and 100 being a suitable image to transform to a TG. The current approach to interpret the score result is a simple qualitative scale with 3 values: Good images > 80%, Fair images 30-79% and Bad images < 30%. Good images are images that can be transformed to TGs. Fair images might work, but the model can't guarantee a good TG with the given image. Bad images are too complex to transform to a proper TG. In Figure 1 you can see examples of suitable and unsuitable images; on the left side there is a high quality image of a dog (highlighted) with a clear outline classified as a suitable image, and on the right side there is an image of a cat (highlighted) with a fuzzy outline classified as an unusable image. To achieve this, we used Mobilenet as the base of our model. Mobilenet is a very light-weight but efficient model [4]. Our model was built on top of Mobilenet because it is a well-proven model suited for classification [4]. We used 500 images from the American Printing House tactile graphics library and also 300 images we gathered through Google image results using the BANA tactile graphics guidelines [12]. We specifically picked images related to animals, to specialize the model in a specific subject. Calibrating the model, the parameters were set to: Learning rate 0.0001, epochs 100 and units 50 (others defaulted) were optimal for our problem. For hyper-parameters, we decided to use $\alpha = 1$ and $\rho = 1$ for the best accuracy [4] (maximum number of output channels and maximum input resolution).

WEB PLATFORM

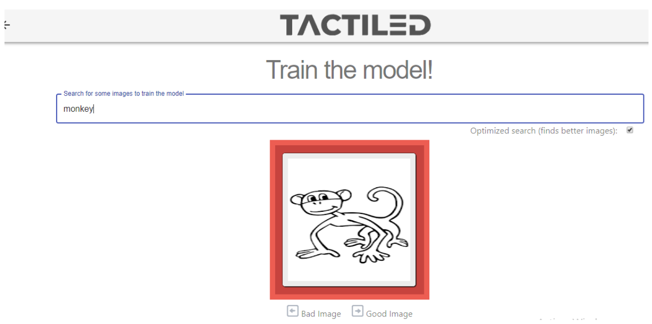

Figure 2. Training page. In this page the expert (TVI) helps training the machine learning model by identifying images that can be transformed to a TG.

We designed a training page where (1) TVIs can access to unclassified images and (2) images uploaded by users to confirm if they are TG-transformable images. As seen in Figure 2, the interface is very simple; the users can access the page and then they can start classifying random images. They can also use the search bar, where they can look for certain concepts to help classify images related to keywords. Afterwards, we use the new data to retrain the model.

We also designed the search page where (1) users can access to classified images and (2) upload an image to evaluate if it is suitable or unusable to transform to a TG. As seen in Figure 3, the users can input a word in a search text box to search for images related to keywords.

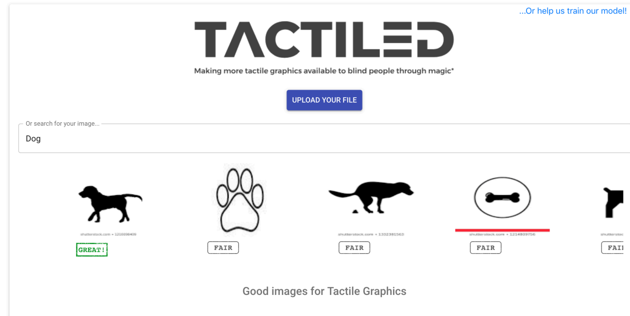

Figure 3. In here you can see the web-platform where you can search for images that can be transformed to TGs and also upload and evaluate your own images.

They can also click on the images to download them and use them to make a TG. Finally, they can access the classification function by clicking on the upload button and then selecting an image from their computers.

Figure 4. Evaluation page. Here we can see the result of the classification of an image given by an user. This image is good candidate to be transformed to a TG (score of 100). If the model makes a misclassification the user has the option to reclassify.

The third page we designed is the evaluation page. In here, users (1) see the evaluation result of the image they uploaded to classify (2) download the image (3) access to the training page if the result is incorrect. The result is shown as a score from 0 to 100, 0 being unsuitable and 100 being a suitable image to transform to a TG.

FUTURE WORK

In the future, we will work on improving our ML model by feeding it a bigger database of images, improving the platform usability and upgrading the Mobilenet model to V2. Currently the web-platform only provides images on simple concepts (animals). We plan on creating multiple models to simplify and improve the classification accuracy, by making models specialized on certain concepts (e.g., animals, buildings, maps, objects).

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