Doodle Detection to Spot Level of Autism

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Abstract - *This paper presents a computer based assessment developed to assist people with Autism Spectrum Disorder (ASD). Autism is a spectrum disorder, meaning that someone can be mildly, moderately, or severely autistic. Clinicians diagnose people with autism at level 1, level 2, or level 3. These levels reflect individuals' ability to communicate and adapt to new situations, expand beyond restricted interests and manage their daily life. People at level 1 need relatively little support, while people at level three need a great deal of support from others. In our proposed work, we are doing an assessment application using a touch screen to spot this level. This assessment consists of three different assessment fields to spot the level of autism. The child earns points based on the performance at each level. The severely autistic group will be having lower scores overall. Whereas the people with mild autistic behaviour will be having relatively high scores.*

***Key Words*: Autism Spectrum Disorder (ASD), Doodle detection, Convolutional Neural Network(CNN), QuickDraw**

1. INTRODUCTION

Mental disorders such as Autism Spectrum Disorder (ASD), the name adopted in 2013, is one of the fastest growing developmental delays and has risen by 700% in the last 23 years. They are heterogeneous disorders that are notoriously difficult to diagnose, especially in children. There is no quantitative test that can be prescribed to patients that may lead to definite diagnosis of a person. It is widely known that defining and diagnosing mental health disorders is a difficult process due to overlapping nature of symptoms, and lack of a biological test that can serve as a definite and quantified gold. ASD is a neuro-developmental brain disorder which causes social impairments like repetitive behavior and communication problems in children. More than 1% of children suffer from this disorder and detecting it at early ages can be beneficial. Studies and researches show that some demographic attributes like gender and race vary among ASD and healthy individuals such that males are four times more prone to ASD than females. Diagnosing ASD has been explored thoroughly from different aspects, like monitoring behavior, extracting discriminatory patterns from the demographic information and analyzing the brain data, behavioral data such as eye movement and facial expression.

2. MOTIVATION

Reciprocity can mean the flexibility to work together with others to shape a conversation, a game or other social interaction. Children with autism often struggle with reciprocity, and poor reciprocity is one among the new diagnostic criteria for the disorder. But clinicians lack tools to measure it. The most common method uses interactive drawing to spot signs of autism. For this, the tester and child take turns adding elements such as a house or a tree to a common drawing. The child earns points for contributing to the same feature as the tester does. If a child begins sketching a car and the tester turns it into a school bus, for example, a typically developing child tends to run with the new narrative, adding a student behind the wheel. A child with autism might scratch out the transformed car to keep the drawing in line with his original vision. This cannot be considered as an effective way because the disease cannot be determined only by drawing.

Our idea was to develop a computer aided drawing test by making use of the openly accessible quickdraw dataset. Later on, we identified that drawing alone cannot be used as a criteria for assessing. So we decided to incorporate other areas like memory assessment and object identification skills assessment to our project.

3. IMPLEMENTATION

While most of the existing autism detection techniques focus on interactive drawing to detect the disease, this project tries to focus on other features too, which includes object identification and memory & concentration assessment to predict the level of autism. The assessment proceeds in three levels. First level is an object identification test which assesses the patients' ability to correctly identify a specific type of object amongst a set of objects. Second is a memory and concentration assessment which tests your ability to memorise objects on the screen. Most weightage is given to the third level, which assesses your drawing ability and reciprocity skills.

3.1 Object Identification Test

In this level, a number of objects will be displayed on the screen. The question is to identify a particular object amongst the given objects. For eg, if the question is to identify a bird, for every correctly identified bird the user will be rewarded with 2 points. A wrong selection will decrement your score by 1. For a particular question, there will be 5 correct options and many wrong options. If the user correctly identifies the 5 options he will get a score of 10 points for a question. A set of two questions are present in this level making the maximum score as 20.

3.2 Memory and Concentration Assessment

The second level is a short term memory test. A set of different objects will be displayed on the computer screen for 10 seconds. The user is requested to memorise objects on the screen. After 10 seconds, the current screen will fade and the next screen with a new set of objects appears. The task is to find out the objects that were already present in the previous screen. This round also consists of 2 questions with a score of 10 points each, making a total of 20 points.

3.3 Drawing Assessment

This level has the highest score, ie, 60 points, amongst the three levels. Three questions of 20 points each are given. There will be two canvases on the screen with one coloured green and the other one being white. The task is to draw a particular object (for eg. flower) on the green coloured canvas. To assess the reciprocity skills of the user, the colour of the canvases swaps with time. The user will be rewarded for every adaptation he makes. The idea being used is that people with high levels of autism could not adapt well to the new environment. Even when the colour of the canvas changes, he may still stick on to draw on the initial canvas, forgetting the instruction to draw on the green canvas.

For every question the user will be awarded 15 points for this adaptation and the rest 5 points will be rewarded for the drawing skills. The most technically relevant part of the project lies here. Drawing skills are evaluated using doodle detection technique which uses machine learning to detect if the user has drawn the same object mentioned in the question. An image classifier model was created using tensorflow and keras. The neural network was trained on different classes from Google's Quick Draw dataset.

The Dataset is a collection of 50 million drawings across 345 categories. The drawings were captured as timestamped vectors, tagged with metadata including what they were asked to draw. The downloaded dataset is kept in a folder named 'data'. A CNN model is trained using these image samples. We trained the CNN model with 3 convolutional layers followed by max-pooling and dropout. Two dense layers are used after flattening the network. The number of trainable parameters is shown in figure below.

Table -1: Number of trainable parameters

Layer <type>	Output Shape	Param #
conv2d_1 <Conv2D>	<None, 24, 24, 32>	832
conv2d_2 <Conv2D>	<None, 20, 20, 32>	25632
max_pooling2d_1 <MaxPooling2	<None, 10, 10, 32>	0
dropout_1 <Dropout>	<None, 10, 10, 32>	0
max_pooling2d_2 <MaxPooling2	<None, 5, 5, 32>	0
conv2d_3 <Conv2D>	<None, 1, 1, 64>	51264
max_pooling2d_3 <MaxPooling2	<None, 1, 1, 64>	0
flatten_1 <Flatten>	<None, 64>	0
dense_1 <Dense>	<None, 512>	33280
dropout_2 <Dropout>	<None, 512>	0
dense_2 <Dense>	<None, 128>	65664
dropout_3 <Dropout>	<None, 128>	0
dense_3 <Dense>	<None, 15>	1935
Total params : 178,607 Trainable params : 178,607 Non-trainable params :0		

3.3.1 The raw moderated dataset

The raw data is available as ndjson files separated by category, in the following format:

Key	Type	Description
key_id	64-bit unsigned integer	A unique identifier across all drawings
word	string	Category the player was prompted to draw
recognized	boolean	Whether the word was recognized by the game
timestamp	datetime	When the drawing was created
countrycode	string	A two letter country code of where the player was located
drawing	string	A JSON array representing the vector drawing

Each line contains one drawing. Here's an example of a single drawing:

{

"key _id" : "5891796615823360",
"word": "nose",
"countrycode": "AE",
"timestamp": "2017-03-01 20:41:36.70725 UTC",
"drawing" : [[[129,128,129,129,130,130,131,132,132,...]]]
}

The format of the drawing array is as follows:

```
[
 [ // First stroke
 [x0, x1, x2, x3, . . .],
 [y0, y1, y2, y3, . . .],
 [t0, t1, t2, t3, . . .]
 ],
 [ //Second stroke
 [x0, x1, x2, x3, . . .],
 [y0, y1, y2, y3, . . .],
 [t0, t1, t2, t3, . . . ]
 ],
 . . . // Additional strokes
```

where x and y are the pixel coordinates, and t is the time in milliseconds since the initial point. x and y are real-valued variables while t is an integer. The raw drawings can have vastly different bounding boxes and number of points because of the different devices used for display and input.

3.3.2 The preprocessed dataset

We've simplified the vectors, removed the timing information, positioned and scaled the data. The data is exported in ndjson format with metadata similar to the raw format. The simplification process was:

a. Align the drawing to the top-left corner, to have a minimum value of 0.
b. Uniformly scale the drawing, to have maximum value as 255.
c. Resample all strokes with 1 pixel spacing.
d. Simplify all strokes using Ramer–Douglas–Peucker algorithm with an epsilon value of 2.0.

3.3.3 Get the data

The dataset used for training my model could be found at https://console.cloud.google.com/storage/browser/quickdraw_dataset. The dataset is available as ndjson files separated by category. As an example, to easily download all simplified drawings, one way is to run the command: *gsutil-m cp gs://quickdraw_dataset/full/simplified/*.ndjson*

3.3.4 Training the model

For each class, we took the first 10000 images, and then split them to training and test sets with ratio 8:2. The training/test loss/accuracy curves for the experiment are shown in the chart below:

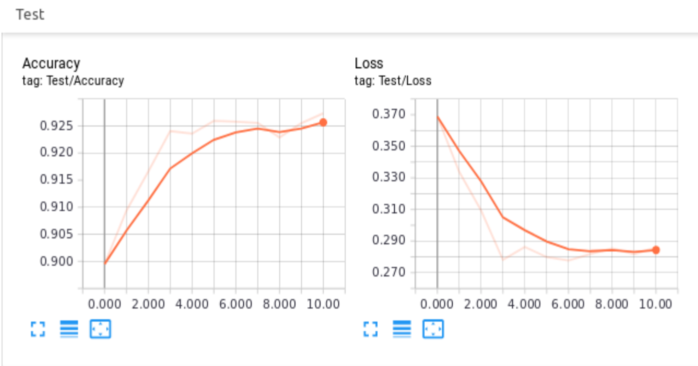

Chart -1: Test loss/accuracy curves

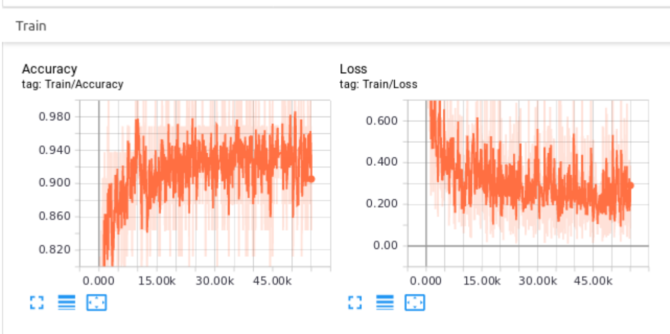

Chart -2: Training loss/accuracy curves

4. FUTURE WORK

More stages of assessment can be incorporated into the project in future. Also,we would like to experiment with advanced CNN architectures such as VGG-Net and ResNet, which have already reached state-of-the-art levels of image classification performance, although not for sketches in particular. Additionally, we have only used approximately 1% of the total Quick Draw dataset, and we believe training our models on the complete dataset would improve accuracy, as well incorporating stroke order information and extract features such as velocity and acceleration.

5. CONCLUSION

The study can be viewed from the perspective of an exploratory analysis. In this paper, we build a multi-class classifier to assign hand-drawn doodles from Google's online game Quick, Draw! into 345 unique categories. By evaluating the model's performance and learned features, we can identify distinct characteristics of the dataset that will prove important for future work.

REFERENCES

[1] Ha, D., & Eck, D. (2017). A neural representation of sketch drawings. arXiv preprint arXiv:1704.03477.

[2] O. Seddati, S. Dupont, and S. Mahmoudi. Deepsketch: deep convolutional neural networks for sketch recognition and similarity search. In Content-Based Multimedia Indexing (CBMI), 2015 13th International Workshop on, pages 16. IEEE, 2015. 14th International Workshop on, pages 16. IEEE, 2016.

[3] https://github.com/googlecreativelab/quickdraw-dataset