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Artificial Intelligence-Based Mobile Application for Sensing Children Emotion Through Drawings

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Abstract. Children go through varied emotions such as happiness, sadness, and fear. At times, it may be difficult for children to express their emotions. Detecting and understanding the unexpressed emotions of children is very important to address their needs and prevent mental health issues. In this paper, we develop an artificial intelligence (AI) based Emotion Sensing Recognition App (ESRA) to help parents and teachers understand the emotions of children by analyzing their drawings. We collected 102 drawings from a local school in Doha and 521 drawings from Google and Instagram. Four different experiments were conducted using a combination of the two datasets. The deep learning model was trained using the Fastai library in Python. The model classifies the drawings into positive or negative emotions. The model accuracy ranged from 55% to 79% in the four experiments. This study showed that ESRA has the potential in identifying the emotions of children. However, the underlying algorithm needs to be trained and evaluated using more drawings to improve its current accuracy and to be able to identify more specific emotions.

Keywords. Mobile Application, Artificial Intelligence, Emotion Sensing, Children.

1. Introduction

Children go through varied emotions such as happiness, sadness, anger, excitement, worry, and fear. At times, it may be difficult for children to express their emotions for a variety of reasons such as: being shy, having a speech disorder, or fearing stigmatization. Children can express their emotions through verbal and physical interactions as well as through art [1]. Understanding the emotions of a child through art can provide another dimension and level of analysis needed to understand a child's emotional well-being [1, 2]. Psychologists use some techniques to help analyze childhood emotions through art: the family drawing Test and the Tree test or Baum test [3]. Over the past five years, there has been a steady growth in the use of technology and AI to analyze emotions. A dearth of research has been conducted on using AI to understand the emotions of children

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through art. We found one study where a researcher developed a deep learning model to detect the emotions of children through their drawings by extracting features representing five emotional states: happiness, anxiety and depression, anger, and violence [4]. The model achieved an accuracy of 87% showing that this technique can help psychology professionals detect child emotions through art [4]. The major limitation of the study was not involving art therapy professionals to help label the data, and this may have led to the improper classification of the drawings and yielded biased results. The researcher also trained and validated the model using a small dataset, which was taken from children with symptoms related to Post Traumatic Stress Disorders [4]. Given that little work has been conducted in this area, we study the use of AI to assess the emotional state of children through Art.

2. Methods

This study included Primary (local) and Secondary (online) data sources for child art drawings. Our primary source was data collected from a local school based in Doha. We collected 102 drawings to test the effectiveness of art therapy-based emotion-sensing. Our secondary data source was searching online where we collected a total of 521 drawings through Google and Instagram.

Due to the limited number of drawings, an art therapist suggested having only two high-level emotional classifications (positive emotions and negative emotions). The positive class included emotions such as happiness, excitement, pleasure, energy, and hope. The negative class included emotions such as sadness, anger, hate, fear, abuse, and disappointment. Thus, the 521 drawings were labeled by the art therapist into two different groups: positive emotions (n=365) and negative emotions (n=258). Drawings collected from the school were also labeled into positive emotions (n=52) and negative emotions (n=50). The drawings in the negative class were labeled as 0 and drawings in the positive class were labeled as 1 for the model.

With regards to the model, the ResNet50 convolutional neural network model was implemented for the classification of drawings. The model was implemented with Python using the open-source Fastai (https://www.fast.ai/) framework. The parameters required for ResNet50 were set by default by the Fastai library and did not require the researcher to optimize the parameters to obtain the results. This study employed transfer learning to train the convolutional neural network. Transfer learning uses a pre-trained model built upon a very large dataset which is then customized for the problem at hand. This technique is useful for a small dataset, which is the case of this study.

For data processing, the drawings were generated on a per-batch basis, with a batch size of 64. This means that the algorithm takes the first 64 drawings from the training set and trains the network. All the drawings were reshaped into 224x224 pixels. The Fastai library has a set of standard transformations designed for photos by default, which were used in this experiment. In addition, data augmentation was applied to the training data where more data can be produced from the existing dataset. For every image in the training set, the model created 9 augmented drawings, which were created from an original image using various augmentation techniques such as cropping, zooming, rotating, flipping, and tilting (Appendix 1)[2]. Three pre-trained models were used for

[2] Appendices are available at GitHub: https://github.com/AHassan2/Artificial-Intelligence-based-Mobile-Application-for-Emotion-Sensing-for-Children-through-Art

training the model: ResNet18, ResNet34, and ResNet50. Further, we implemented an algorithm that helps us illustrate the layer activations that classify an image as having positive or negative emotions. A heatmap was produced highlighting the layers that find patterns that lead to the activation of the image as being classified as positive or negative.

We conducted four different experiments using different primary and secondary datasets combinations. In the first experiment, this model was trained and tested on the primary (local dataset) which contains the school drawings using ResNet34. This was our smallest dataset containing only 102 drawings collected from the school. The data was split into 80-20% for training and test set, respectively. About 20% of the data from both positive and negative classes constituted the test set, which included a total of 21 drawings. The training set had 65 drawings while the validation set had 16 drawings.

In the second experiment, our model was trained and tested on the secondary (online dataset). This set constituted a total of 521 drawings collected from both Google drawings and Instagram. We split the data into 80% and 20% for training and the test set, respectively. The test set had a total of 104 drawings. The training set and validation set had 334 and 83 drawings, respectively. In the third experiment, the model was trained on the local dataset but tested on the online dataset. The local dataset had 102 drawings from the school. Twenty percent of the drawings were included in the validation set which contained 21 drawings and the remaining 81 drawings were included in the training set. Randomly 40 drawings from the online dataset were selected to represent the test set. In the fourth experiment, the model was trained on the online dataset and tested on the local dataset. The online dataset had 521 drawings in total out of which 417 drawings constituted the training set and 104 drawings the validation set. The entire local dataset was used as the test set for this experiment.

3. Results

The model in all experiments achieved an accuracy between 55% and 79% (Table 1). The sensitivity of the model in the experiments ranged between 33% and 86%. The model achieved specificity in the experiments between 46% and 83%. The precision of the model in the experiments varied between 60% and 74%. The corresponding algorithm to obtain the intermediate layer activations and heatmap illustration was used only for experiment two. The algorithm was not implemented in Experiment 1 because the school drawings varied largely from each other in terms of shapes or colors. Experiments 3 and 4 did not employ this algorithm as the accuracies obtained for these two experiments were insufficient. With the layer activations, the particular pixels of the image that was responsible for the prediction of that image as positive or negative were highlighted. These highlighted areas illustrate what shape or color had been studied by the model and classified as either positive or negative. One obvious pattern that was observed from the heatmaps was that of the detection of the yellow color as positive (Appendix 2) and the red color as negative (Appendix 3).

Table 1. The model performance in the four experiments

Experiments	Training dataset	Testing dataset	Model	Epochs	Accuracy	Sensitivity	Specificity	Precision
1	Primary	Primary	ResNet34	10	76%	33%	83%	67%
2	Secondary	Secondary	ResNet50	20	79%	86%	46%	74%
3	Primary	Secondary	ResNet34	15	62%	73%	51%	60%
4	Secondary	Primary	ResNet18	25	55%	44%	74%	60%

4. Discussion

This research aimed at developing a deep learning model for emotional sensing using drawings. While the model achieved good accuracy in Experiments 1 and 2, its accuracy was moderate in Experiments 3 and 4. This moderate accuracy may be attributed to the considerable variations between school drawings and online drawings. Specifically, while the online drawings were well-drawn, detailed, and full of colors, the school drawings were mainly unclear black and white sketches and shapes.

Certain patterns could be observed from the drawings that were labeled as positive or negative. Bright colors, flowers, trees, and greenery depicted positive clues, whereas, war vehicles, weapons, and hospitals depicted negative cues. One contradiction was seen with the color red. Red was used in both positive and negative drawings. But, red was mainly seen as blood, fire, or danger in negative drawings. Therefore, the model learned the color red as negative and started predicting every picture with red as negative.

The proposed app can be used by teachers and parents to understand emotions of children, thereby, developing strategies to customize guidance and mentorship according to their emotions. The underlying algorithm needs to be trained and evaluated using more drawings to improve its accuracy and to be able to identify more specific emotions.

To the best of our knowledge, this is the second study that has developed a deep learning model to detect the emotions of children through their artwork. Previous work [4] classified children's emotions into five categories (happiness, anxiety and depression, anger, and violence) and achieved a training accuracy of 87%. However, the previous work (1) did not involve an expert (e.g., an art therapist) to label the data, (2) did not report details about the data processing or the algorithms used for that study, and (3) trained and validated the model using a small dataset [4].

One of the main limitations of our paper is that drawings were labelled by one art therapist, thereby, we could not assess how accurate art therapists are in labelling the drawings. However, it is more likely that the art therapist's labelling was accurate given her extensive experience in this field.

5. Conclusions

ESRA can help parents and teachers understand the emotions of children through analyzing their drawings using AI. However, the underlying algorithm proposed in this work needs to be trained and evaluated using more drawings to improve its current accuracy. Further research is needed to improve ESRA in identifying more emotions and considering cultural nuances in the representation of the drawings.

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