ISSN 2278-3091
Volume 8, No.1.6, 2019
International Journal of Advanced Trends in Computer Science and Engineering
Available Online at http://www.warse.org/IJATCSE/static/pdf/file/ijatcse6381.62019.pdf
https://doi.org/10.30534/ijatcse/2019/6381.62019

A Deep Learning Approach in Robot-Assisted Behavioral Therapy for Autistic Children

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ABSTRACT

A significant percentage of the world's children are being diagnosed with Autism Spectrum Disorders (ASD every day. According to the most recent reports for Disease Control Data (DCD), ASD affects one in 68 children in the US only. It has been recognized as a neurological disorder characterized by difficulties in social communication and social interaction; abnormal body posturing; repetitive movements and self-abusive behavior. There is no cure for ASD but efforts to mitigate difficulties in social functioning, learning, and to improve quality of life of persons with ASD is usually through behavioral therapy. Robot-assisted behavioral therapy is one emerging field that provides intervention mainly for children with ASD, so far, only to augment traditional rehabilitation approaches. In this approach, robots have been used for different purposes such as for behavior eliciting, rehearsing skills, and improving interaction and socialization skills. Nonetheless, there are still a lot to be done in developing robots that can effectively work towards improving social and emotional confidence in children with ASD. This paper sheds light on recent studies that utilize deep learning technique and sets out to propose a deep learning-based emotion detection system for humanoid robots to enhance robot awareness during therapy sessions. We present a model of the emotion-aware robot-assisted therapy which is expected to ease the prediction and recognition for the emotion and behaviors of autistic children and enhance robot intervention during rehabilitation. It was found that the proposed DL model when tested on an improved trial dataset of normal subjects has increased the accuracy of detection. However, while new deep learning technologies for facial expression recognition algorithms could lead to higher detection accuracy, it is clear from that the size and reliability of the data will be the success factor in this study.

Key words: deep learning; autism; ASD; robotic; machine learning, humanoid robot

1. INTRODUCTION

Autistic children have a brain development disorder which affects their communication and social behaviors [1]–[6]. There are several numbers of diagnosis and rehabilitation tools which are dedicated for ASD treatment. For instance, Autism Diagnostic Observation Schedule-Revised (ADOS-R) and Autism Diagnostic Interview (ADI) [3], [7] are two common methods used for ASD diagnosis. Furthermore, since the social robots have been utilized in the education and treatment enormously, the use of robots for rehabilitation and education of individuals with ASD is increasing. Most of the recent literature has reported that the utilization of robots give a positive impact on the treatment of autistic children [8]–[12]. However, autistic children suffer from profound impairments in social interactions and communication. While therapists face a big challenge in traditional autism therapy, none of the robotic-based techniques provide intelligent multimodal solutions. Thus, the finding of an intelligent multimodal-autonomous robotic rehabilitation scheme remains limited in the treatment of autistic children. Further studies are required to formulate a robot's DL-based multimodal algorithm based on image processing techniques in autism therapy that can help in extracting, tracking, and monitoring the children’s behaviors.

In this paper we propose Convolutional Neural Network (CNN) architecture for emotion recognition to improve facial expression detection and consequently a humanoid-based, facial expression-aware rehabilitation system for children of ASD. The rest of this paper is structured as follows: Section 2 describes machine learning and deep learning techniques and their use in the diagnosis and management of ASD. Section 3 proposes a new method of using DL to improve ASD treatment and finally the paper is concluded in Section 4.

2. MACHINE LEARNING FOR ASD

Machine learning has been utilized for ASD diagnosis by training a large set of images, a dataset of pre-diagnosed patients and healthy participants. The training dataset should be identified and manipulated such as reducing the image size by selecting a limited number of image features. The goal of this manipulation is to select the best features of the dataset and simplifying the data processing complexity such as reducing computing cost during the process. In order to perform this manipulation process, some software packages are used such as WEKA [12]. That dataset usually is generated using diagnostic tools such as Autism Diagnostic Observation Schedule (ADOS) [13], and Autism Diagnostic Interview-Revised (ADI-R) [7]. ADOS and ADI-R are considered the gold standard in diagnosis of ASD [14].

Autism Diagnostic Observation Schedule (ADOS) [13] is considered as one of the main screening methods for an individual with ASD in different age groups utilizing a structured set of activities with a certain module. ADOS has been used in clinical practices for ASD and Pervasive Developmental Disorder (PDD) diagnoses [15]. With ADOS, the behaviors of individuals are evaluated in terms of language, movement and social interactions which rate the traits and levels of PDD and Autism [15].

Autism Diagnostic Interview-Revised (ADI-R) is an interview-based tool in which the individuals' parents are interviewed by a clinician. The basic use of ADI-R is for distinguishing between the individuals affected and non-affected by ASD and PDD. During the interview, the participants will be given 93 questions mainly focusing on the child's behavior [7]. The answers to such questions are scored by the expert clinician in two main ranges, from 0 to 3 and from 7 to 9. Zero indicates normal cases, from 1 to 3 represents the level of the disability, light to extreme. In cases of total disability, not applicable, and not known, they are represented by the values 7, 8, and 9 respectively [16].

2.1 Deep Learning for ASD

Deep Learning is a subset of Machine Learning with great power and flexibility, it is considered as a promising tool that can be utilized in ASD treatment especially after computer processing speed improvements. Thus, the Deep Learning techniques become more applicable to train high dimensionality models. Therefore, Deep Learning applications have attracted increasing attention recently from researchers. Deep Neural Networks (DNNs) is an example where DL has been successfully applied for feature extraction using texts, images, and audio [17][18][19]. In terms of ASD, the DL has been applied in diagnosis of individuals who suffer from ASD and classify ASD in addition to controlling the patients according to their extracted activities. Furthermore, DL methods are applied in different goals for ASD, utilizing large samples of patient's images such as Autism Imaging Data Exchange I (ABIDE I) [20], Cohn-Kanade (CK and CK+) dataset [21] and the Japanese Female Facial Expression (JAFFE) [22]. Based on these dataset of different DL models have been trained successfully.

2.2 Convolutional Neural Network (CNN)

CNNs is designed basically for image recognition where the used images are divided and processed as compact topological portions to detect particular patterns [23].

CNN or ConvNet is one of the most common algorithms in Deep Learning that can learn the features of ASD by utilizing low level attributes to extract high level [24] [25]. CNN networks are used in image and video applications such as objects/ image detection and recognition. Through CNN, the different inputs of images/videos can be trained to analyze and understand their contents. While CNN has been exploited well in the computer vision field which has achieved advanced and promising results, it is typically formulated for 2D images. Several studies have used CNN for 3D images by working on 2D videos and considering time as the 3rd dimension [26] [27].

2.3 Application of DL in ASD

In the study [28], Koyamada et al. used Deep Neural Networks (DNN) to read brain states from measurable brain activities [28]. The networks have been trained as two hidden layers followed by a softmax output layer, where seven categories (Emotion, Gambling, Language, Motor, Relational, Social and Working Memory) related to the tasks of fMRI data have been classified from 499 subjects. The result of that model reported 50% mean accuracy which outperforms the results from supervised learning models (48%) [29]. In [30], the researchers have also used deep learning to train models on images of patients for classifying the individual with schizophrenia versus matched healthy controls, and patients with Huntington disease versus healthy controls. Three hidden layers were used in their network including 50 nodes in both of the first and second layers, while in the top layer, 100 units have been used. The classification accuracy in their model reported 90% for features extracted from three Deep Belief Network (DBMs), while the classification accuracy using raw data in a Support Vector Machine is 68%.

Likewise, in the study [31] Deep Learning was used to identify the disease and categorize the level of severity into high, medium and low. A large dataset includes 2641 images of patients and 859 of healthy controls from different countries were used. The network in that study has three hidden layers, with 50 nodes in first and second layers, and 100 in the top layer.

2.4 Expression Detection

The work in [32] summarizes various techniques of Deep Learning used and it can be considered a useful reference for studies of various deep learning techniques in facial recognition system. Obtaining a high accuracy of emotion detection is the main objective in DL facial emotion detection. In [33], the combination of feature extraction and optimization of face images component analysis has been reported to achieve this goal. Both aforementioned works focus on normal person facial expression. In another related work to enhance the facial emotion detection, [34] the cropping of the image in the region called facial action unit (AU) has been found to improve the performance of detection.

It is a common view that the ASD child are less expressive when it comes to producing facial expressions. In the work [35] by Trevisan D. A. et al., a study was conducted to investigate if ASD children produces facial expressions differently as compared to a control group. They found that the ASD child is less expressive of their emotion and slower to react in their response [35]. In another study, researchers found that a pipeline approach can improve the analysis of facial expression for ASD child [36]. Their method consists of five main components that includes a face detector, a facial landmark detection and tracking block, a head pose estimation and eye gaze tracking block, a facial action unit intensity estimator and a high-level semantic data analysis module [36]. The system claims to be able to be more accurate than autism experts in analyzing facial expressions.

2.5 Related works

In a previous study on ASD facial behaviour [37], the detection of uncontrolled behavior and facial expression for ASD can be used as markers for early screening and intervention planning for their pre-school. The basic approach for facial recognition using CNN is also used in the work by Haque et al. [38] for identifying the ASD child emotion using FER2013 Dataset. In their work, the difference in lighting used on images collected for the dataset had improved the test accuracy, wherein the brighter the image the higher the accuracy achieved. Comparatively the dark images are more prone to false identification.

According to the recent reports, ASD affects children with varying disability levels from very mild to severe [8], [39]. Robots are exploited numerously in different assistive scenarios such as to fulfill the various roles of human-need and to aid in the rehabilitation of individuals with ASD.
Here is a summary of the most recent studies done. In [40] a framework was proposed based on the deep neural network to enable integrated learning of interactive behaviors for normal participants including audio. A large amount of training data was handled with significant dimensionality. Another study [41] has been conducted to explore the significance and impact of the deep learning techniques applying for CT brain images classification, therefore from its results, the deep learning technique facilitates the extraction for signature information rooted in both 2D slices and 3D blocks of CT images.

In [29], deep learning and the ABIDE dataset have been used to identify autism spectrum disorder (ASD) patients by utilizing a large dataset of brain imaging. In that study, 70% was reported as an achieved accuracy of identification of ASD. Moreover, a deep learning model has been used in [42] to recognize the emotional information of respiration. That model was conducted on the DEAP and Augsburg dataset, where the accuracy results of the DEAP and Augsburg datasets are 77% and 80% respectively.

The next section will describe the proposed deep learning approach for facial expression detection based on seven emotional states.

3. METHODOLOGY

3.1 Dataset

The improvement in the modern processors opens the gate for the researchers to exploit Deep Learning to predict the emotion recognition from human facial expression. The different proposed DL models have been trained on a large number of images to fulfil two main objectives, which are to mitigate the computational complexity, and to increase the accuracy of the emotion recognition. Such models can be trained on a different dataset (a large number of images) such as Deep Lesion used as medical image datasets, CK+ Dataset, and FER-2013 dataset for emotion recognition. Since none of these datasets are dedicated for emotional recognition in autistic children, a dataset of autistic children images will need to be developed to be used as a training dataset for emotion recognition. The different facial images of children with ASD will be collected under the supervision of a specialist. The collected data will be manipulated and processed before the training phase. Each image is filtered and cropped to be normalized into a specific pixel size.

As the ASD dataset is still in the process of being developed, we preliminarily tested the system using our own trial dataset of normal subjects and results are discussed in Section 4.

3.2 DL Model Development

In this paper, Convolutional Neural Network (CNN) has been proposed to recognize the facial expression of autistic children. As shown in Figure. 1, in addition to the input and output layers which are a 32×32 pixel image and seven output facial expressions respectively, the network architecture of this CNN comprises five hidden layers which are as follows: in the first layer, the convolution of CNN layer will be done with 5×5 kernel and 32 images as of 28×28 pixels. The next layer is used to reduce the parameters for the network by reducing the image's size using max pooling of 2×2 kernel size. The third layer is a convolution layer with a kernel of 7×7 which is followed by max pooling of 2×2 kernel size to reduce the parameters. The outputs of this layer are fully connected to the last hidden layer of 256 neurons. The output layer includes seven nodes which represent the human facial expressions. Based on the study of LeCun [20], the goal of the first layer is to extract the basic facial features such as edges, eyebrow, corners, lips, and end points. As in the same study, the max-pooling is used in the second layer where the pixels are subsampled to make the image smaller which reduces the number of parameters. Similar to the first and second layers, the next two layers are dedicated for facial feature extraction and subsampling, but instead of basic shape extraction, low level feature extraction is performed, namely contextual element extraction. The outputs of the fourth hidden layer is fully connected to the last hidden layer which is the extracted features of the facial expressions. Stochastic Gradient Descent (SGD) algorithm [32] will be used for weight calculations of every neuron in this network. The SoftmaxWithLoss function will be used to calculate the loss, whereas the Rectified Linear Unit or ReLu will be used as the neurons' activation function which is considered as a faster learning function in deep networks [33].

3.3 Algorithm and implementation

Figure. 2 depicts the proposed system that comprises two main components: the PC server and the rehabilitation side which include the humanoid robot and display screen. Firstly, in the PC server side, the system will be initialized with pre-processing steps, that aim to: detect the face from the autistic children datasets; and remove non-expression specific features of a facial image. Training the dataset of autistic children will be performed by the proposed CNN networks on the PC server using Caffe on Graphics Processing Unit (GPU).

On the other side, there is the rehabilitation room, which combines a humanoid robot with a speaker, microphone, Wi-Fi connector, HD camera, and display screen. The humanoid robot connects with the PC server to receive the stream of captured images in real time with high accuracy and low frame rate. High accuracy images are required to get accurate expression detection while the frame rate would be low in order to match the processing complexity on the PC server side. Thus, the streamed frames are manipulated on the PC server side to the CNN network which detects the embedded emotion expression in the input images. The humanoid robot initializes with a common social robot's module such as a greeting module, then it could proceed to a story telling module or a module which displays some colored photos. This is performed coinciding with streaming the frames to the PC server which sends back one emotional state (label) of the participant, out of the seven, as the output of the CNN network. The received emotion tells the robot whether to continue or to change the current module to another module while continuing to monitor the participant's emotion expression by streaming the images to the PC server. The CNN network produces one output of seven categories of emotional states, namely happy, neutral, angry, disgusted, fearful, sad, and surprised. However, in our initial context of emotion awareness, the humanoid robot will interpret them into one of two states; positive emotion which may indicate the autistic subject's interest to continue the session; or negative emotion which may signify a need to change modules or stop the session altogether. Thus, happiness and neutral emotions are interpreted as positive emotion, whereas anger, disgust, fear, sadness are interpreted as negative emotion.

According to the received emotion state, the humanoid robot would proceed to select a suitable a pre-programmed module to play to the autistic subjects. The modules are designed by trained therapist and switching of modules based on subject's emotional state will also be programmed based on therapist recommendations.

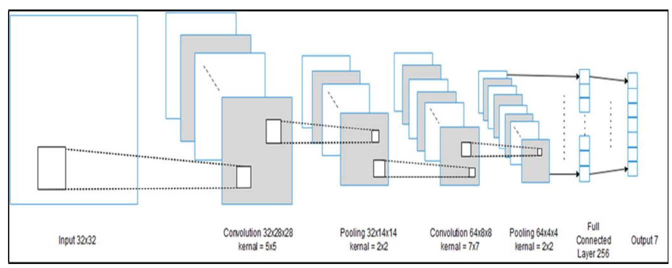

Figure 1: Proposed Convolutional Neural Network (CNN) architecture for emotion recognition from the facial expression of the autistic children. Including five hidden layers (two convolution layers, two subsampling layers, and one fully connected layer) in addition to the input and output layers

4. PRELIMINARY RESULTS

Prior to developing the facial expression dataset of autistic children, a facial expression dataset of normal subjects was developed. The dataset was collected from internet and prepared for use in training the proposed DL model. This dataset contains 276,305 high quality images and was used as a trial dataset in this work. The idea is to start with a process for which data is easily obtained so as to gain experience and to develop appropriate hypotheses that can lead to real and significant benefits.

The new DL model which was developed based on VGGNet architecture network was trained on an i7 PC successively using this dataset. The proposed model was found to achieve high accuracy facial expression recognition on the trial dataset, achieving up to 83.5% accuracy. Previous works on facial expression detection trained on a smaller dataset (FER-2013) reported a recognition accuracy of only 65.6%. This shows that datasets play an important role in the success of machine learning applications and understanding the success criteria for autistic facial expression dataset will be an important step to undertake in this study.

Although new deep learning technology for facial emotion recognition algorithms can lead to higher accuracy in detection, it is clear that the size and quality of data will deliver the result we anticipate. In view of the fact that the ASD child is less expressive than the normal child, the reliability of data will very much depend on good quality images and expert labeling.

5. CONCLUSION

In this paper, we have reviewed state-of-the-art Machine Learning and Deep Learning and their application in emotion recognition. Additionally, we have proposed a new Deep Learning-based emotion recognition system to be used in autism rehabilitation treatment. Both Deep Learning technique and humanoid robot are used to perform the emotion recognition and train the children with Autism Spectrum Disorder (ASD). In this system, the DL model based on Convolutional Neural Network (CNN) using Caffe library and OpenCV for image processing are applied on a GPU. In the proposed system, a Deep Learning expression detection method is integrated with humanoid-assisted rehabilitation therapy for autistic children. It is believed that the combination of a reliable dataset for facial expression of children with ASD and the proposed DL model, can enhance the robot-based behavioral therapy for the children with ASD. Such a robotic-based visual rehabilitation strategy will effectively contribute to improve: a) the child's engagement during the learning sessions, b) child's imitation ability based on robot's gestures and voice, c) child's interaction and communication skill. While new deep learning technologies for facial expression recognition algorithms could lead to higher detection accuracy, it is clear that only a large and reliable specialized dataset will provide the necessary results.

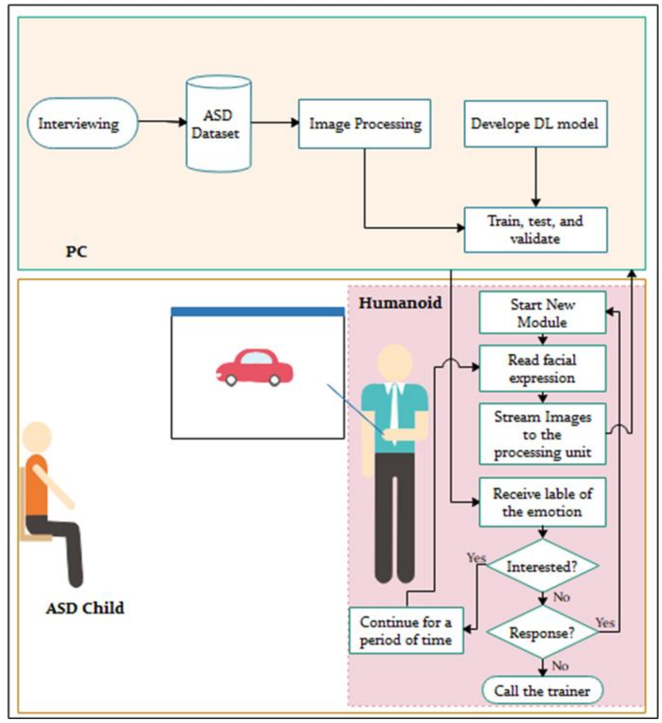

Figure 1: Robotic-based rehabilitation system for autistic children using Convolutional Neural Network (CNN)

ACKNOWLEDGEMENT

The authors would like to thank the Ministry of Education (MOE) Malaysia for providing the grant 600-IRMI/FRGS 5/3 (150/2019), and the Research Management Centre (RMC) of Universiti Teknologi MARA for supporting this research work.

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