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Technology-Assisted Emotion Recognition for Autism Spectrum Disorder (ASD) Children: A Systematic Literature Review

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ABSTRACT The information about affective states in individuals with autism spectrum disorder (ASD) is difficult to obtain as they usually suffer from deficits in facial expression. Affective state conditions of individuals with ASD were associated with impaired regulation of speech, communication, and social skills leading towards poor socio-emotion interaction. It is conceivable that the advance of technology could offer a psychophysiological alternative modality, particularly useful in persons who cannot verbally communicate their emotions as affective states such as individuals with ASD. The study is focusing on the investigation of technology-assisted approach and its relationship to affective states recognition. A systematic review was executed to summarize relevant research that involved technology-assisted implementation to identify the affective states of individuals with ASD using Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) approach. The output from the online search process obtained from six publication databases on relevant studies published up to 31 July 2020 was analyzed. Out of 391 publications retrieved, 20 papers met the inclusion and exclusion criteria set in prior. Data were synthesized narratively despite methodological and heterogeneity variations. In this review, some research methods, systems, equipment and models to address all the related issues to the technology-assisted and affective states concerned were presented. As for the consequence, it can be assumed that the emotion recognition with assisted by technology, for evaluating and classifying affective states could help to improve efficacy in therapy sessions between therapists and individuals with ASD. This review will serve as a concise reference for providing general overviews of the current state-of-the-art studies in this area for practitioners, as well as for experienced researchers who are searching for a new direction for future works.

INDEX TERMS Affective state, emotion recognition, frontal facial image, autism.

I. INTRODUCTION

Individuals with Autism Spectrum Disorder (ASD) is widely known to have difficulties with socio-emotion interaction, suffering from communication disorder and emotional dysregulation, together with rigid and repetitive behaviors [1]. These difficulties can lead to problems related to performance of expressive language, social, and emotional adaptive skills [2]. All individuals diagnosed with ASD, experience either one or more aforementioned difficulties regardless of the severity levels of diagnosis [3].

In the aspect of emotions, it is reported that individuals with ASD usually do not show the emotions in a way that normal people would able to recognize and understand. It is either they do not respond emotionally, or their emotional responses might sometimes seem over overreaction [4].

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TABLE 1. The research question and motivation.

NO.	QUESTION STATEMENT	MOTIVATION
RQ1	What are the stimuli used in invoking corresponding emotions?	Every emotion can be induced by different types of stimuli, which can be in various forms. The motivation here is to induce specific emotion using specific stimuli that is suitable for ASD children. The nature of the stimuli is based on locality or demographics.
RQ2	How features from raw data were extracted in order to evaluate measure the affective states of ASD children?	Technology-assisted approaches usually started with data acquisition process. In this stage, the data collected are normally large and need to be reduced into a manageable dataset. Selection of features are essential as it will reflect the accuracy of the emotion recognition process.
RQ3	What are the existing approaches to address affective states using technology-assisted approach?	The objective is to perceive and investigate what are the possible methodologies, strategies, and algorithms to measure affective states of ASD children.

With the addition of difficulty in expressing their emotion verbally, thus, in return, the individuals with ASD often exhibit many behaviors that their family, teachers, and caregivers find challenging. This situation would become worse when the individuals with ASD is a child, as children might have limited vocabulary and acquire more assistances in their daily activities from adults. For example, an ASD child is reaching out for help as she is in pain, however, she fails to express the pain emotion either through speech or facial expressions, thus being misunderstood by the caregiver whose response would not address the situation. Therefore, it is essential for the ASD children caregivers to understand, interpret the situation and react to the child accordingly.

With the advancement of today technology, these challenges can be reduced. There are many research that have been embarked around recognizing human emotions, particularly for autistic children [5], [6] and individuals [7], however, not all of them is based on real-time, automated emotion recognition process. Most of the developed research in the field leveraged on the experienced therapists or psychologists to evaluate and classify the ASD individuals' emotions manually. The process is tedious, time consuming and challenging to be used by the ASD individuals' family, teachers, and caregivers, hence posed significant constraints to address the issue effectively.

Thus, the aim of the study is to report a systematic analysis from the literatures involving the use of technology to recognize the affective states of individuals with ASD. The analysis explains and discusses the conducted experiments, reviews the results of the intervention and assesses the validity of the data. This study also aims at discussing suitable methodologies and features to be used from human emotion recognition research when considering the subject to be ASD children in particular.

II. METHODOLOGY

In order to conduct a thorough analysis of technology-assisted approach for the ASD affective states, a systematic review was conducted based on the guideline provided by Kitchenham [8] that adopted the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) approach.

The step-by-step process involved in systematic analysis of the literatures are discussed in this section. It started with enumeration of research questions that were intended to be answered in the study, followed by the description of search strategy for Systemic Literature Review (SLR) source materials collected from different online databases. This includes the explanation about the inclusion and exclusion criteria used for the screening of the non-relevant works over related materials, and finally described the process by which data was extracted to answer the research questions.

A. RESEARCH QUESTIONS

In this study we concentrate on the role of technology-assisted approaches in recognizing affective states among ASD children. Therefore, the following research questions (Table 1) were formulated and framed to help carry out a detailed review on the topic.

B. SEARCH STRATEGY

1) LITERATURE SOURCES

We have chosen to use the following main digital publication databases to cover the research topic as broad as possible, as listed in Table 2.

TABLE 2. Database online sources.

No.	Source	URL ACCESS
1.	IEEE Xplore	ieeexplore.ieee.org
2.	Science Direct	sciencedirect.com
3.	Scopus	scopus.com
4.	Wiley	onlinelibrary.wiley.com
5.	Springer Link	link.springer.com
6.	Google Scholar	scholar.google.com

TABLE 3. Keywords used in the search.

TERM 1	TERM 2
• ASD children	• Emotion
• Autis* (autism or autistic)	• Affective states
• Child* (children)	• Psychological states

The databases were chosen based on these three criteria:

(1) covering engineering and computer science topics
(2) published in journals and conference proceedings
(3) the subscribed databases cover up-to-date technology related

2) SEARCH STRINGS

Suitable keywords are important in order to drive efficient searching. Inaccurate keywords may mislead the search and result in irrelevant literature. Therefore, several search terms and their combinations were identified in the process and reported in this section. The search was focused on the English language publications.

The main search terms together with their alternatives terms used in the search query are reported in Table 3.

It is noteworthy to mention that the search also included the publications from social science, health science and humanities related fields.

3) SEARCH PROCEDURES

With the search queries that were built based on the search strings discussed in the previous section, the general literature searching procedure was executed that follows four main steps which were identification stage, screening stage, eligibility stage and inclusion stage.

a: IDENTIFICATION STAGE

In the identification stage, six commonly-used online databases were utilized for the searching purposes, namely IEEE Xplore, Science Direct, Scopus, Wiley, Springer Link and Google Scholar. Separate searches were conducted in each of the online databases by using the search queries as shown in the following TABLE 4.

The search results from each of the online databases were downloaded and gathered as accumulated prospective studies. As the *Mendeley*® software is used for analysis purposes, these accumulated prospective studies were imported to *Mendeley*®. *Mendeley*® is a reference management application. It facilitates in managing the references according to the essential information such as citations with bibliography, synchronization with Digital Object Identifier (DOI), and metadata for further analysis.

b: SCREENING STAGE

As the search was done separately in each of the online databases, the possibility of having same research articles in the accumulated literature searching was high. Therefore, the screening stage was needed to exclude the duplicates. The step was done in *Mendeley*®.

After that, the title and abstract screenings were carried out. The process was done one-by-one, starting with the title screening and followed by the abstract screening. The focus was more on the main keywords of the research topics which were children, autism and emotion.

c: ELIGIBILITY STAGE

Although the title and abstract screening stages excluded the irrelevant research articles, it was still important to access the full text of the research articles for eligibility purposes.

d: INCLUSION STAGE

At the final stage of the search procedure, the accumulated prospective studies were narrowed down with the inclusion and exclusion set forth in line with the research topic. The inclusion and exclusion criteria are discussed in the next section.

Lastly, the quality assessment was executed. This stage was essential as it acts to control the quality of prospective studies especially in terms of accuracy, relevance and credibility of the selected primary research articles.

C. STUDY SELECTION

In order to include only relevant and quality research articles in the systematic literature review, the relevant studies were carefully selected by using the steps illustrated in Figure 1.

The literature selection was conducted by four-stage process. Stage 1 included all the search output from each electronic database which was combined in Mendeley®. Stage 2 involved removing the duplicates. Stage 3 was on the eligibility of full-text assessed. Stage 4 was based on inclusion and exclusion criteria as listed TABLE 5.

Based on the searches conducted in the online databases, there was 375 prospective research articles. Apart from that, an additional record also identified from reference lists, and that added 16 more research articles. Therefore, the total number of prospective studies was 391.

The duplicates were then omitted in the first screening stage, which resulted in 17 research articles omitted and the new number reduced the prospective studies to 374.

After that, the research articles were screened for their title and abstract in order to include only the research articles

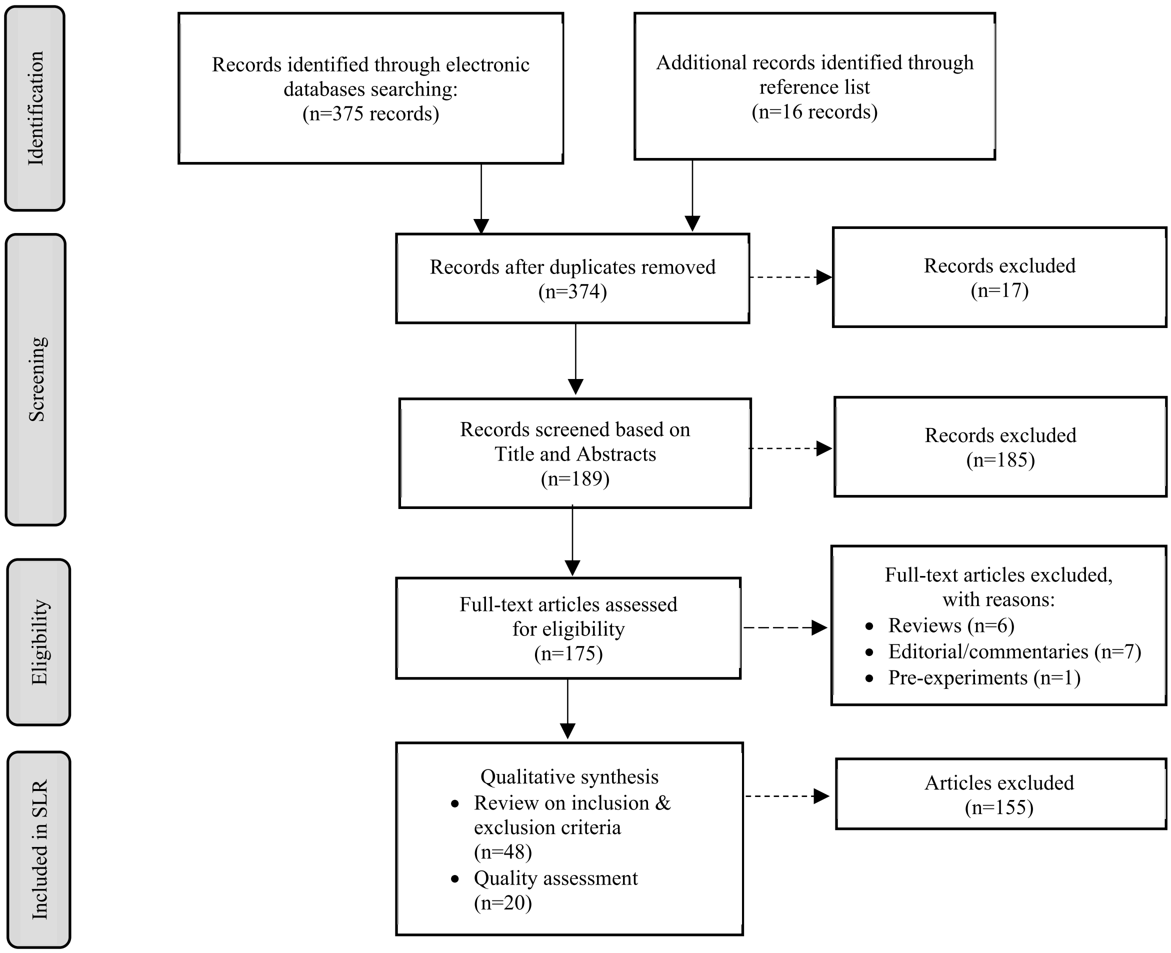

FIGURE 1. PRISMA flow diagram.

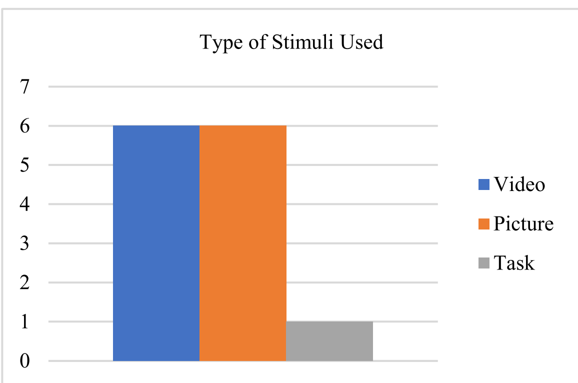

FIGURE 2. Types of stimuli used.

that were relevant to the research topic. Thus, the prospective studies were further reduced to 189.

Next, with the consideration of the full text, the total of the prospective studies further dropped to 175.

In the subsequent process, the research articles were assessed by using the inclusion and exclusion criteria as listed in TABLE 5.

The collective selection process reduced the prospective studies to 48.

It is noteworthy to mention, years spanning from 2000 to 2020 was selected as inclusion criteria as there was a growing interest in ASD research under Centre for Disease Control (CDC) when it was established in 2000. CDC has setup the Autism and Developmental Disabilities Monitoring (ADDM) network that provide a one stop center of information specifically for ASD individuals. Thus, enormous data on ASD individuals were easily available to the researchers from the initiative.

Lastly, the quality assessment was done to measure the quality of contents presented in the prospective studies as shown in TABLE 6. In order to evaluate prospective studies, the following quality assessment questions were created:

1. Q1: Are the objectives clearly defined?
2. Q2: Is the methodology clearly described?
3. Q3: Are the features extraction clearly described?
4. Q4: Are the research finding clearly reported?
5. Q5: Are future works included?
6. Q6: Is the main subjects is ASD children?

In terms of scoring, each of the questions can have 3 possible scoring which were 1 mark for "yes", 0.5 mark for "partially" and 0 for "no". The total marks for each prospective study were summed up to indicate the quality of the study.

TABLE 4. Database and search procedure.

DATABASE	QUERY	REMARKS	HITS
IEEE Xplore	Advance search: autis* AND “affective states” OR emotion	Filter Year: 2000-2020 Document type: Journal and Conferences	75
Science Direct	Advance search: (autism OR ASD) AND ("affective states" OR emotion) AND children	Filter Year: 2000-2020 Article Type: Research articles and Conference Abstracts	77
Scopus	Advance search: TITLE-ABS-KEY((ASD OR autism) AND ("affective states" OR affective OR emotion OR emotional) AND (facial OR face))	Filter Document Type: Article and Conference Paper Language: English	17
Wiley	Advance search: (autis*) AND (emotion OR “affective states”) anywhere	Filter Year: 2000-2020 Filter Publication Type: Journals Open access content	10
Springer Link	Normal search: autis* AND emotion* AND "affective states" AND NOT (survey)	Discipline: Computer Science Years: 2000-2020	61
Google Scholar	Advance search: • with the exact phrase: autis* "affective states" child* emotion facial • without the words: survey moebius mouse breastfeeding	Custom range: 2000-2020 Exclude: patents	135
Additional Records	Identified through reference list		16
		TOTAL	391

TABLE 5. The selection criteria.

NO.	ID	CRITERIA
Inclusion	IN1	Studies published over the last 20 years, between 2000 to 2020.
	IN2	Journals articles and conference papers
	IN3	Research related to engineering and computer sciences field only
	IN4	A search which addresses specific approach to identify affective states on ASD only
Exclusion	EX1	Papers which are published before 2000.
	EX2	Duplicate papers are also disregarded
	EX3	Studies with an exclusive focus on medicine or ASD diagnosis.
	EX4	Research that focuses on usability of user interface where technology is not involved
	EX5	Exclude studies that did not reporting on affective states classification (Eg. Pilot study)
	EX6	Exclude studies that includes other than ASD. Eg. ADHD, Asperger syndrome

TABLE 6. Quality assessment of the primary studies.

ASSESSMENT	STUDIES	Q1 OBJECTIVE	Q2 METHOD	Q3 FEATURES	Q4 FINDINGS	Q5 FW	Q6 ASD	TOTAL MARKS
Author 1	[9]	0.5	1	1	1	1	0	4.5
Author 1	[10]	0.5	1	1	1	0.5	0.5	4.5
Author 1	[11]	0.5	1	1	1	0.5	1	5
Author 1	[5]	0.5	1	1	0.5	0	0.5	3.5
Author 1	[12]	1	0.5	0.5	1	1	0.5	4.5
Author 1	[13]	1	0.5	0	0.5	0.5	1	3.5
Author 1	[14]	0.5	1	0	1	0.5	0.5	3.5
Author 1	[15]	1	0.5	1	0.5	1	0.5	4.5
Author 1	[16]	0.5	1	1	1	0	0.5	4
Author 1	[17]	1	1	1	1	0.5	0.5	5
Author 1	[18]	1	1	1	1	1	1	6
Author 1	[19]	0.5	0.5	1	0.5	0	1	3.5
Author 2	[20]	0.5	0.5	1	0.5	0	1	3.5
Author 2	[21]	0.5	0.5	1	0.5	0	1	3.5
Author 2	[22]	0.5	1	1	1	0.5	1	5
Author 2	[23]	1	0.5	0.5	1	1	1	5
Author 2	[24]	1	1	0.5	1	1	1	5.5
Author 2	[25]	0.5	1	1	1	1	0	4.5
Author 2	[6]	0.5	1	1	1	0.5	1	5
Author 2	[26]	0.5	1	1	1	0.5	0	4
Author 2	[4]	0.5	1	0	0.5	0.5	0.5	3
Author 2	[27]	0.5	1	0.5	0.5	0	0.5	3
Author 2	[28]	0	1	0.5	1	0	1	3.5
Author 2	[29]	1	0.5	0	0	1	1	3.5
Author 3	[30]	0.5	0.5	0	1	0.5	0.5	2.5
Author 3	[31]	0.5	0.5	0.5	0.5	0.5	1	3.5
Author 3	[32]	0	1	1	1	0.5	0	3.5
Author 3	[33]	0	0.5	1	1	1	0	3.5
Author 3	[34]	0	1	0.5	0.5	0.5	0.5	3
Author 3	[35]	0	0.5	0.5	0.5	0	0.5	2
Author 3	[36]	0	0.5	0.5	1	1	0	3
Author 3	[37]	0	0.5	1	0.5	0	1	3
Author 3	[38]	0	0.5	0.5	1	1	0	3
Author 3	[39]	0.5	0	0.5	1	0	0.5	2.5

TABLE 6. ***(Continued.)*** **Quality assessment of the primary studies.**

ASSESSMENT	STUDIES	Q1 OBJECTIVE	Q2 METHOD	Q3 FEATURES	Q4 FINDINGS	Q5 FW	Q6 ASD	TOTAL MARKS
Author 3	[40]	1	1	0	0	0.5	0.5	3.0
Author 3	[41]	0	1	0.5	1	0	1	3.5
Author 4	[42]	1	0.5	0	0	1	1	3.5
Author 4	[43]	0.5	0.5	0	1	0.5	0.5	2.5
Author 4	[44]	0	0.5	1	1	1	0	3.5
Author 4	[45]	0	1	0.5	0.5	0.5	0.5	3
Author 4	[46]	0	0.5	0.5	0.5	0	0.5	2
Author 4	[47]	0	0.5	0.5	0.5	0	0.5	2
Author 4	[48]	0	0.5	0.5	1	1	0	3
Author 4	[49]	0	0.5	1	0.5	0	1	3
Author 4	[50]	0	0.5	0.5	1	1	0	3
Author 4	[51]	0	0.5	0.5	1	1	0	3
Author 4	[52]	0.5	0	0.5	1	0	0.5	2.5
Author 4	[53]	1	1	0	0	0.5	0.5	3.0

Four authors of the paper performed the qualitative assessment of the studies. The authors were randomly assigned to the studies.

Each author also performed the inter-rate assessment in order to increase the credibility of the quality assessment and to minimize individual preferences. If there were a dispute occurred in the inter-rate assessment, the reviewers' team would resolve the disagreement before consensus was found. The exclusion of each literature was accompanied with a reason, and recorded. The inter-rate assessment table is illustrated in TABLE 7.

With the completion of the search process, there were 20 selected primary studies relevant to this systematic literature review, and presented in TABLE 8.

D. DATA EXTRACTION

In order to extract the information from the previous works, data extraction process was applied to show the synthesis of the existing works. Essential information was then extracted from these previous works, which were; the literature (i) title, (ii) authors, (iii) publication year, (iv) publisher, (v) type of publications, (vi) field, (vii) abstract, (viii) stimuli used, (ix) features, (x) classifier, (xi) number of subjects involved, (xii) subject characteristics, (xiii) sensors used, (xiv) stimuli database, (xv) training database, (xvi) emotion classes, (xvii) reported performance and as well as (xviii) future works.

III. RESULTS & FINDINGS

The summary of selected primary studies in terms of number of subjects involved, subject characteristics, sensors used, and emotions classes are presented in TABLE 9, while the other details, including stimuli used, features, classifier, stimuli database, training database and reported performance, are presented in TABLE 10.

After reviewing all the selected primary studies, several data were extracted in order to answer the following research questions:

A. RESEARCH QUESTION 1: WHAT ARE THE STIMULI USED IN INVOKING CORRESPONDING EMOTIONS?

All studies in the literature used various types of stimuli to invoke corresponding affective states in their intended applications. The evoked affective states were based on a model of six basic emotions proposed by Ekman [54] [55]; fear, anger, joy, sadness, disgust, and surprise.

Figure 2 and TABLE 7 illustrate the types of stimuli used in the selected primary studies. Video stimuli refers to

TABLE 7. Inter-rate assessment.

ASSESSMENT	STUDIES	Q1	Q2	Q3	Q4	Q5	Q6	TOTAL MARKS
Author 1	[31]	0.5	0	0.5	0.5	0.5	1	3
Author 1	[32]	0	1	0.5	1	0.5	0	3
Author 1	[29]	0.5	0	0	0	1	1	2.5
Author 1	[33]	0	0	1	1	1	0	3
Author 2	[34]	0	0.5	0.5	0.5	0.5	0.5	2.5
Author 2	[44]	0	0.5	1	1	0.5	0	3
Author 2	[41]	0	0.5	0.5	0.5	0	1	2.5
Author 2	[42]	0.5	0.5	0	0	1	1	3
Author 3	[5]	1	1	1	0.5	0	1	4.5
Author 3	[12]	1	0.5	0.5	1	1	1	5
Author 3	[13]	1	1	0	0.5	0.5	1	4
Author 3	[14]	1	1	0	1	0.5	0.5	4
Author 4	[19]	0.5	0.5	1	0.5	0.5	1	4
Author 4	[20]	0.5	0.5	1	0.5	0.5	1	4
Author 4	[21]	0.5	0.5	1	0.5	0.5	1	4
Author 4	[28]	0	1	0	1	0	1	3

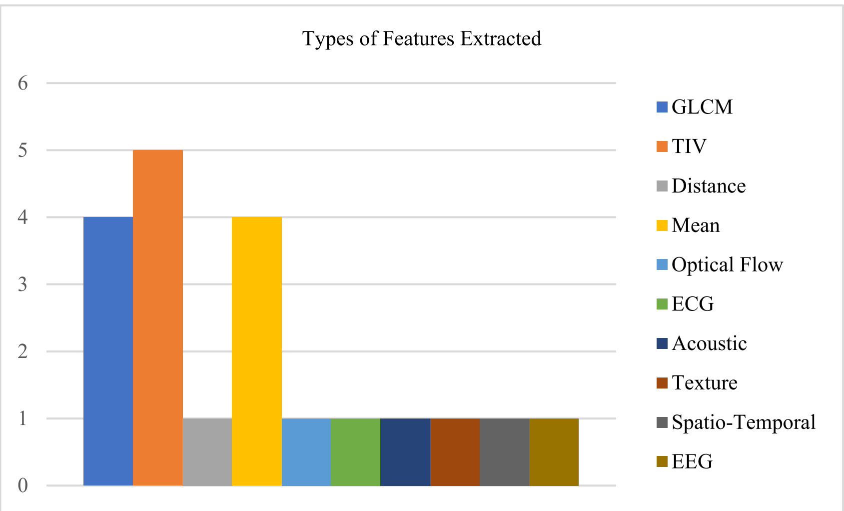

FIGURE 3. Types of feature extraction used.

bi-sensory stimulation that combines audio and visual stimulus in order to elicit the target emotion. On the other hand, picture stimuli contain a series of images that invoke the result of the desired emotions. There were static images that mostly

TABLE 8. The selected primary studies.

REFERENCES	*STUDIES*
[9]	GLCM Correlation Approach for Blood Vessel Identification in Thermal Image
[10]	Hottest pixel segmentation based thermal image analysis for children
[11]	Implementation of Wavelet Analysis on Thermal Images for Affective States Recognition of Children with Autism Spectrum Disorder
[5]	Mean of Correlation Method for Optimization of Affective States Detection in Children
[12]	Emotional State Analysis Through InfraRed Thermal Imaging
[13]	Atypical asymmetry for processing human and robot faces in autism revealed by fNIRS
[14]	Overview of social cognitive ability from the perspective of facial expressions and context - Estimating emotion based on context essays and facial expressions
[15]	Virtual Reality-Based Facial Expressions Understanding for Teenagers with Autism
[16]	Assisting the autistic with improved facial expression recognition from mixed expressions
[17]	Emotion recognition system for autism disordered people
[18]	A Kalman filtering framework for physiological detection of anxiety-related arousal in children with autism spectrum disorder
[19]	Facial emotion recognition system for autistic children: a feasible study based on FPGA implementation
[20]	Hardware efficient FPGA implementation of emotion recognizer for autistic children
[21]	Low complexity FPGA implementation of emotion detection for autistic children
[22]	A Speech Emotion Recognition Solution-based on Support Vector Machine for Children with Autism Spectrum Disorder to Help Identify Human Emotions
[23]	Emotion Detection of Autistic Children Using Image Processing
[24]	A comparative study of Autistic Children Emotion recognition based on Spatio-Temporal and Deep analysis of facial expressions features during a Meltdown Crisis
[25]	Classifying affective states using thermal infrared imaging of the human face
[6]	Integration of Facial Thermography in EEG-based Classification of ASD
[26]	Texture descriptors based affective states recognition-frontal face thermal image

adopted from well-recognized database such as International Affective Picture System (IAPS) database. Meanwhile, task stimuli were directive real-life situation that elicited the desired emotions. For example, the subject was instructed to think of happy place in order to invoke happy emotion.

The most common stimuli used was video and pictures, which were used in six studies respectively. Meanwhile only one study was using task-based stimuli. As there were 20 studies selected in total, out from them were seven studies that did not report the stimuli used in their research work as they directly utilized image database to train their classifiers and did not developed their own image databases.

As for videos stimuli, most of the studies used videos associated to the affective states needed. For instance, a cheerful cartoon video was used in order to invoke happy emotion in the ASD children. There were also studies that used static images from the databases and converted them into video series to stimulate the required emotion [11], [25].

As for picture stimuli, four studies; [6], [7], [9], [23] used the same images from IAPS database. The IAPS database is a standard and mostly referred database in emotion induction.

B. RESEARCH QUESTION 2: HOW FEATURES FROM RAW DATA WERE EXTRACTED IN ORDER TO MEASURE THE AFFECTIVE STATES OF ASD CHILDREN?

As all methods documented in the literature employed a typical framework for classification stage, they needed to set several features to feed these classifiers.

Based on 20 selected primary studies, there were several features that commonly-used as tabulated in TABLE 12.

In general, the features used as reported in the literatures can be classified into GLCM, thermal intensity value (TIV), distance, mean, optical flow, ECG, acoustic, texture, spatio-temporal and EEG features.

Based on TABLE 12, the most frequently used features were TIV, followed by GLCM and mean value. Five papers

TABLE 9. **Primary studies.**

REFERENCES	NO. OF SUBJECTS	SUBJECT CHARACTERISTICS	SENSOR USED	EMOTION CLASSES
[9]	16	Children age (7.5 ±1.5) years old. Subjects are children without social interaction difficulties and healthy.	FLIR thermal camera model T420	5 emotions: happy, surprise, anger, fear, disgust.
[10]	7	3 children, 4 adults	FLIR thermal camera model T420	2 emotions: happy, sad
[11]	57	TD and ASD children, age 5-9 years old	FLIR thermal camera model T420	3 emotions: happy, fear, sad
[5]	16	Children age (7.5 ±1.5) years old. Subjects are children without social interaction difficulties and healthy.	FLIR thermal camera model T420	5 emotions: happy, surprise, anger, fear, disgust.
[12]	5	TD children (three girls and two boys), Ages between 9-11 years old (M: 10.2 and SD: 0.84) Absence of phobias or traumatic experiences, neurological disorders and medicine taking; exclusion: usage of glasses).	Therm-App® - long infrared wavelength (LWIR) between 7.5 - 14 lm) at 8.7 Hz frame rate	2 emotions: happy, sad
[13]	20	8 males with a diagnosis of ASD and 12 non-ASD (neurotypical) males. Children and adult. All participants were between the ages of 7 and 36 (NT: M = 14.5, SD = 10.76; ASD: M = 15.6, SD = 9.55).	Functional near-infrared spectroscopy (fNIRS)	2 levels of heoglobin: Oxygenated (HbO) and deoxygenated (HbR)
[14]	14	Japanese normal children N = 14, 8 boys and 6 girls, age range 11 year and one month to 17 years and 8 months (mean ± SD = 13 ± 2 years old)	Near-infrared spectroscopy (NIRS)	4 levels based on Oxy-Hb concentration: congruent, incongruent, pleasant, and unpleasant
[15]	20	A total of 10 high functioning subjects with ASD (M: n=8, F: n=2) of ages 13 – 17 (M=14.7, SD=1.1) and an age matched 10 TD (M: n=8, F: n=2) controls of ages 13 – 17 y	Physiological signal. i.e., heart activity (ECG), blood volume changes, skin temperature, skin response, Muscle activity (EMG), respiration: BioNomadix wristgear by Biopac Inc. Eye tracker: Tobii X120	2 levels: ASD subjects when they were correctly identifying the emotions vs. when they were not able to identify the emotions
[16]	200	Both male and female and age varying from 18 to 60 years	NR	6 emotions: happiness, surprise, fear, disgust, sadness and anger
[17]	NR	NR	EEG head gear	6 emotions: happy, sad, anger, distress, surprise, and fear
[18]	24	ASD children , age 11.7+2.8, male: female 17:7	ECG wrist gear	2 emotions: anxiety, normal
[19]	NR	NR	NR	6 emotions: Neutral, Happiness, Sadness, Surprise, Anger, Disgust, Fear
[20]	NR	NR	NR	7 emotions: neutral, happiness, sadness, surprise, anger, disgust and fear

TABLE 9. *(Continued.)* Primary studies.

[21]	NR	NR	NR	7 emotions: neutral, sadness, happiness, angry, surprise, disgust, fear
[22]	24	24 professional actors (12 males, 12 females) participated in the recording process	NR	7 emotions: anger , disgust, fear, happy, 11eutral, sad, surprised
[23]	NR	NR	NR	4 emotions: Angry, Neutral, sad and Happy
[24]	23	ASD, 6-15 years old.	Kinect v2 camera	4 emotions: anger, sad, disgust, fear – meltdown vs normal
[25]	12	12 able-bodied asymptomatic adults (9 females) of varying ethnicity (mean age 24.0 ± 2.9 years)	3 kinds of sensors: - Respiratory belt - Thermal infrared camera (FLIR Systems ThermaCAM (Model SC640) long wavelength infrared (LWIR) - Photoelectic Blood Pulse Volume (BVP) sensor	6 binary classification tasks: - high arousal (HA) versus baseline (BASE), low arousal (LA) versus BASE, high valence (HV) versus BASE, low valence (LV) versus BASE, HA versus LA, and HV versus LV
[6]	17	10 male, 7 female ASD/Non-ASD Age range: 5-17 years old	Thermal & EEG	NR
[26]	30	15 males, 15 females. Aged 21-28 years old mean age: 23 years old	FLIR T420 thermal camera - long-wave infrared (LWIR)	6 emotions: disgust, angry, fear, happy, sad, surprise

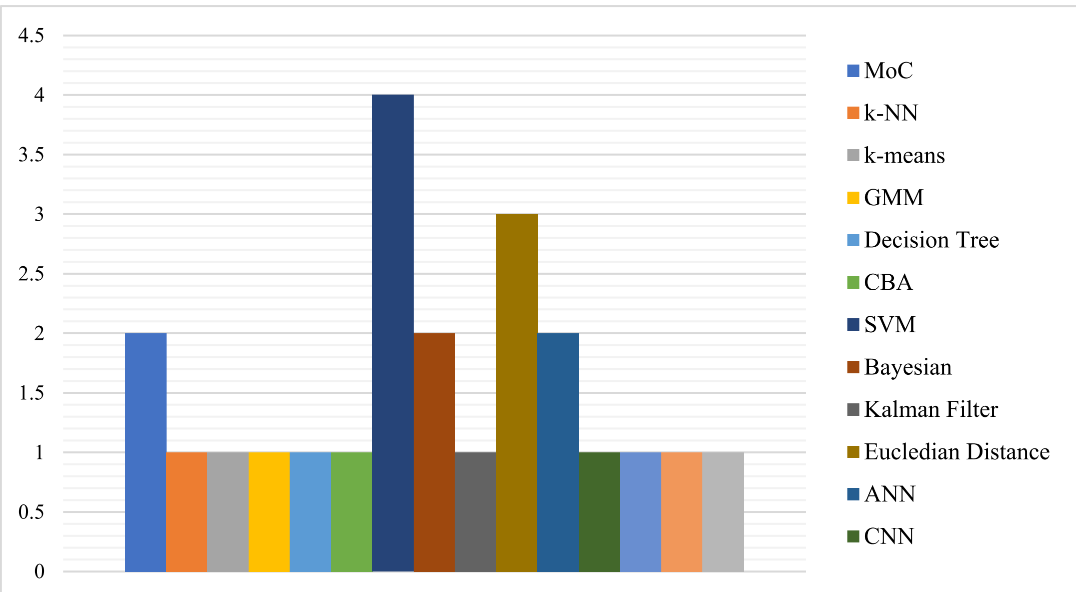

FIGURE 4. Types of classifier used.

used TIV as main features to be extracted from the input thermal images acquired by the thermal camera.

There were several studies that combined the features in order to increase the accuracy of the system

TABLE 10. Primary studies: Evaluation parameters and outcome.

REFERENCES	STIMULI USED	FEATURES	CLASSIFIER	STIMULI DATABASE	TRAINING DATABASE	REPORTED PERFORMANCE
[9]	pictures	GLCM	MoC	IAPS database	NR	Accuracy: 99%
[10]	pictures	TIV	NR	IAPS database	NR	NR
[11]	video	TIV & GLCM	k-NN classifier	IAPS database	NR	Accuracy: 88%
[5]	pictures	GLCM	MoC	IAPS database	NR	Accuracy: 99%
[12]	videos	TIV	Self-assessment	SP - internet	NR	SAM Analysis: Positive video has high mean value Negative video has low value
[13]	pictures	NR	NR	UNR Robotics Research Lab, the Yale Social Robotics Lab, and the USC Interaction Lab - of human face and robot face	NR	In this exploratory test, both groups showed similar asymmetry patterns for the robot faces.
[14]	pictures	NR	NR	SP (of happy & disgust)	NR	NR
[15]	VR	Distance	k-means and GMM	self prepared	NR	55%-80%
[16]	videos	Optical flow	Decision Tree, Component Based Analysis	CDAC, Kolkata which contained one of the six basic expression	NR	NR
[17]	NR	Mean	SVM Bayesian network	NR	CK+database	Accuracy 86.6
[18]	Task, video	ECG	Modified Kalman Filter	self prepared activities: color word interference test, public speaking	NR	Anxiety related arousal in these children with sensitivity and specificity of 99% and 92%, respectively
[19]	NR	Mean	Euclidean distances clustering	NR	JAFFE	82.3 % detection accuracy
[20]	NR	Mean	Euclidean distances clustering	NR	JAFFE	72.9 accuracy
[21]	NR	Mean	Euclidean distances clustering	NR	NR	NR
[22]	NR	Acoustic	SVM	NR	RAVDESS	SVM 67.1 % Logistic Regression 42.6 % Perceptron 32 % Decision Tree 42.5 %
[23]	NR	Texture	ANN, SVM	NR	SP: google, 25 images of autistic children	NN: 0.70 accuracy, SVM : 0.90 accuracy
[24]	NR	Spatio-temporal	CNN	NR	SP: 59 videos, 36 meltdown, 23 normal	Clasification rate 91.27%
[25]	pictures	TIV	Fisher Linear Discriminant Analysis (LDA)	IAPS database	SP	Accuracy: 75%-80%
[6]	NR	EEG, TIV	Naive Bayes, Random Forest, Logistic Regression, Multi-Layer Perceptron Neural Network	NR	NR	Accuracy range: 64-94%
[26]	video	GLCM	SVM	SP	SP	Mean classification accuracy=98.6%

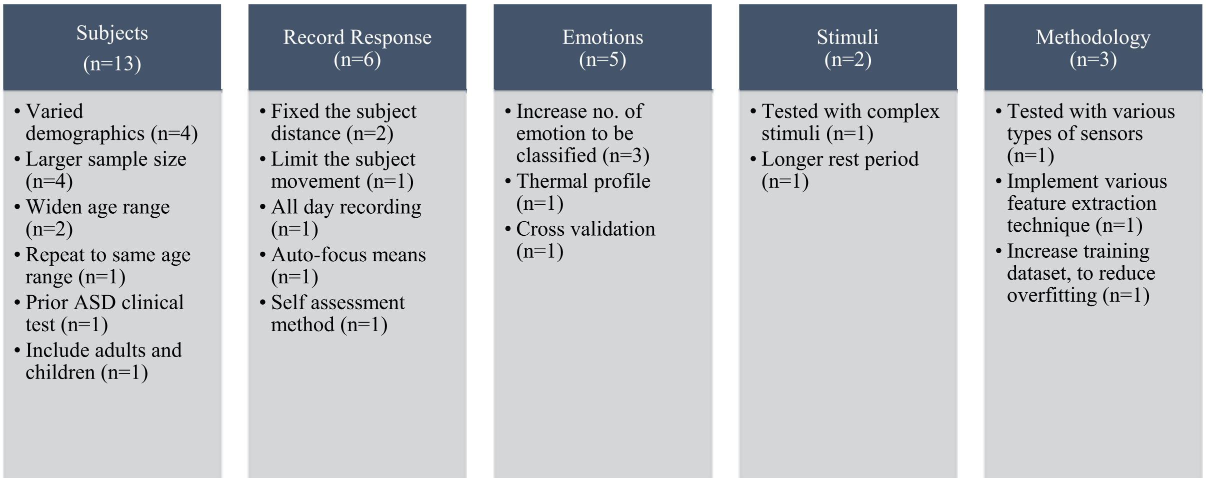

FIGURE 5. Clusters of future research based on the primary studies.

TABLE 11. Stimuli used in the selected primary studies.

STIMULI	SELECTED STUDIES
Video	[11], [12],[15], [16], [18], [26]
Picture	[5], [9], [10], [13], [14], [25]
Task	[18]

TABLE 12. Extracted features.

FEATURES	SELECTED STUDIES
GLCM	[9], [5], [11], [26]
Thermal Intensity Value (TIV)	[6], [10]–[12], [25]
Distance	[15]
Mean	[17], [19]–[21]
Optical Flow	[16]
ECG	[18]
Acoustic	[22]
Texture	[26]
Spatio-Temporal	[24]
EEG	[6]

performance [8], [22], [24]. Figure 3 shows the features used in the selected primary studies, while considering these combinations as individual type of features.

The full list of abbreviations was listed in TABLE 13.

C. RESEARCH QUESTION 3: WHAT ARE THE EXISTING TECHNOLOGY-ASSISTED APPROACHES TO ADDRESS AFFECTIVE STATES?

In the selected primary studies, there were 13 different types of approaches used and the approaches were listed in TABLE 14 and Figure 4.

By referring to the TABLE 14, it can be concluded that most studies utilized Support Vector Machines (SVM) classifier to classify the affective states [17], [22], [23], [26], followed by Euclidean distance clustering and Bayesian network.

TABLE 13. List of abbreviations.

TERM	MEANING
AAM	Active Appearance Model
ANN	Artificial Neural Network
ASD	Autism Spectrum Disorder
CNN	Convolutional Neural Network
DBM	Deep Boltzmann Machines
EDA	Electrodermal activity
GLCM	Gray-level co-occurrence matrix
HOG	Histogram of Oriented Gradient
HSV	Hue Saturation Value
IAPS	International Affective Picture System
k-NN	k-Nearest Neighbours
LBP	Local Binary Patterns
MoC	Mean of Correlation
NN	Neural Network
NR	Not Reported
RBF	Radial Basis Function
SP	Self-prepared
SVM	Support Vector Machine
TD	Typical Developed
TIV	Thermal Intensity Value

TABLE 14. Approaches to classify affective states.

APPROACHES	SELECTED STUDIES
Mean of Correlation (MoC)	[5], [9]
k-NN	[11]
k-means	[15]
GMM	[15]
Decision Tree	[16]
CBA	[16]
SVM	[17], [22], [23], [26]
Bayesian	[6], [17]
Kalman Filter	[18]
Euclidean Distance	[19]–[21]
ANN	[23]
CNN	[24]
LDA	[25]

IV. CONCLUSION AND FUTURE WORK

The systematic literature review describes the development of literatures in emotion recognition that using technology-assisted on autistic children. The selection of literatures from year 2000 to 2020 from six online databases were done to answer the research questions and garner insight of the suitable solutions for emotion recognition in ASD children.

The results of this systematic literature review have provided meaningful answers to our research questions. With the completion of all the stages in systematic literature review process, we found 20 most relevant studies, in which that the following conclusion were derived;

1. Most of the studies used picture and video stimuli to invoke the intended affective states
2. Most of the studies utilized thermal intensities, GLCM and mean value as the distinctive features
3. Most of the studies employed SVM classifier to differentiate between emotions

A. LIMITATION

Inevitably, the findings of the systematic literature have several limitations bounded by:

1. The scope of the findings was within the search keywords and terms
2. Selected databases
3. Selected time frame, spanning from 2000 to 2020
4. Inclusion and exclusion criteria

These limitations may have restricted other studies to appear on the primary selected list. However, the search criteria were decided carefully so to provide useful insight and guidance for practitioners and researchers for further exploratory in this field as comprehensive possible.

B. FUTURE WORK

Clusters of future work for the selected primary studies are illustrated in Figure 5. Generally, there are six clusters observed which are: (1) subject, (2) record response, (3) types of emotions, (4) stimuli, (5) methodology, and (6) applications.

Among 20 selected primary studies, 13 of them suggested that the future work may include the improvement in the terms of subjects [12], [25]. Four of them recommended to set sample size larger, for more than 20 peoples [13]. There were also four studies suggested the future research to include variation in subject demographics, by which the subjects tested should come from different social paradigms [9]. Other suggestions for future works in the subject cluster were to widen the age range that may include both children and adults, prior confirmation of ASD and reconfirm with the system, and repeat the experiment to the same age group of subjects. [10].

Next cluster is record response. There is a total of six primary studies that suggested future work associated with this cluster. Two of them stressed on the importance of fixing the distance for all subjects from the measurement devices. Other study suggested that the recording should be conducted throughout the day as the emotion was fluctuating from time to time. There was also suggestion to use self assessment method concurrently while the recording was done. Other suggestions in this cluster were to limit the subject movement and building any means that able to set the recording in real-time, auto-focus setting [25].

In the aspect of emotions, a few primary studies have recommended to generalize more type of emotions. There were also suggestions to cross validate the data obtained from voice with human facial recognition and consider the thermal profile for each emotion.

As stimuli is an important measure to invoke the subject's emotion, several studies have recommended to develop stimuli for compound emotion rather than just developing basic emotion based stimuli. There was also a primary study that suggested to increase the rest period between each stimulus. For example, the rest period to be set to 12-15 seconds instead of having only less than 8 seconds, in which this would allow the emotion to return to the initial baseline [13].

In terms of methodology, several primary studies suggested to have larger training dataset in order to overcome the overfitting problem [22]. As for sensors and features extraction methods, a few of primary studies have recommended to test the algorithm with different sensors and feature extraction techniques respectively.

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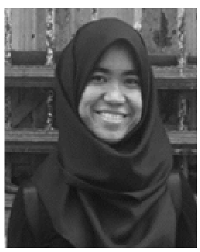

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