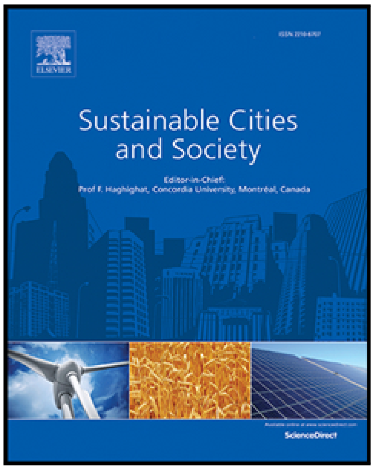
Journal Pre-proof



Artificial Intelligence and Internet of Things in Screening and Management of Autism Spectrum Disorder

Tapotosh Ghosh, Md. Hasan Al Banna, Md. Sazzadur Rahman, M. Shamim Kaiser, Mufti Mahmud, A.S.M. Sanwar Hosen, Gi Hwan Cho

PII: S2210-6707(21)00467-4
DOI: https://doi.org/10.1016/j.scs.2021.103189
Reference: SCS 103189

To appear in: *Sustainable Cities and Society*

Received date: 17 March 2021
Revised date: 7 June 2021
Accepted date: 15 July 2021

Please cite this article as: Tapotosh Ghosh, Md. Hasan Al Banna, Md. Sazzadur Rahman, M. Shamim Kaiser, Mufti Mahmud, A.S.M. Sanwar Hosen, Gi Hwan Cho, Artificial Intelligence and Internet of Things in Screening and Management of Autism Spectrum Disorder, *Sustainable Cities and Society* (2021), doi: https://doi.org/10.1016/j.scs.2021.103189

This is a PDF file of an article that has undergone enhancements after acceptance, such as the addition of a cover page and metadata, and formatting for readability, but it is not yet the definitive version of record. This version will undergo additional copyediting, typesetting and review before it is published in its final form, but we are providing this version to give early visibility of the article. Please note that, during the production process, errors may be discovered which could affect the content, and all legal disclaimers that apply to the journal pertain.

© 2021 Published by Elsevier Ltd.

Journal Pre-proof

Highlights:

- Thoroughly reviewed the efficacy of AI and IoT in screening and managing autism.
- Discussed the integration of smart city facilities for autistic people.
- Challenges in autism screening and management have been discussed.
- Research scopes in this field have been pointed out and described.

Journal Pre-proof

Journal Pre-proof

Artificial Intelligence and Internet of Things in Screening and Management of Autism Spectrum Disorder

Tapotosh Ghosh[a,1], Md. Hasan Al Banna[a,1], Md. Sazzadur Rahman[b,*], M. Shamim Kaiser[b], Mufti Mahmud[c], A. S. M. Sanwar Hosen[d], Gi Hwan Cho[d,*]

[a] *Department of Information and Communication Technology, Bangladesh University of Professionals, Dhaka 1216, Bangladesh*
[b] *Institute of Information Technology, Jahangirnagar University, Dhaka 1342, Bangladesh*
[c] *Department of Computer Science, Nottingham Trent University, Nottingham NG11 8NS, U.K.*
[d] *Division of Computer Science and Engineering, Jeonbuk National University, Jeonju 54896, South Korea*

Journal Pre-proof

Abstract

Autism is a disability that obstructs the process of a person's development. Autistic individuals find it extremely difficult to cope with the world's pace, can not communicate properly, and unable to express their feelings appropriately. Artificial Intelligence (AI), Machine Learning (ML), and Internet of Things (IoT) are used in several medical applications, and autistic individuals can be assisted using the proper use of automated systems. In this paper, some of the research works in the field of application of AI, ML, and IoT in autism were reviewed. State-of-the-art articles were collected and around 58 articles were selected which have significant contribution in this field. The selected research works were analyzed, represented, and compared. Finally, incorporation of the autism facilities in smart city environment is described, some research gaps and challenges were pointed out, and recommendations were provided for further research work.

Keywords: Autism, Smart city, Machine Learning, Internet of Things,

*Corresponding author. Md. Sazzadur Rahman (sazzad@juniv.edu) and Gi Hwan Cho (ghcho@jbnu.ac.kr).

Email addresses: `sazzad@juniv.edu` (Md. Sazzadur Rahman), `ghcho@jbnu.ac.kr` (Gi Hwan Cho)

[1] Tapotosh Ghosh and Md. Hasan Al Banna contributed equally

Journal Pre-proof

Artificial Intelligence, Monitoring

1. Introduction

Autism is a neurological disorder that results in slow brain development. Autistic individuals find difficulty communicating with others, learning new things, expressing their emotions, adapting to a new situation, and so on. They become isolated from the society as they are unable to interact properly with others [1]. They can not understand other's behavior and intention, and they have difficulty thinking outside of their routine [2]. Autism Spectrum Disorder (ASD) [3] and Attention Deficit Hyperactivity Disorder (ADHD) [4] are two kinds of autism that are commonly observed. Autistic individuals face difficulties from early childhood to the rest of their life. They need special schooling, special sessions, and a special way of interaction and understanding. It is not possible to cure autism, but different therapies such as speech, emotion-focused, behavioral may improve their condition and bring them to the core part of the society. In Hongkong, 372 children out of 10000 children are autistic [5]. The autism rate is quite higher in South Korea, the United States, Japan, Ireland, Switzerland, Canada, and Denmark. Table 1 exhibits the number of autistic children per 10000 children in developed countries.

Recent technologies that are based on AI [6], ML [7] and IoT [8] have proved their capabilities in helping in real-life applications. These can be also used for autistic individuals to make their life easier. Early detection of autism can ensure children's timely therapy that can take him to the core part of the society. This can be achieved by the processing power of AI and ML. For instance, autistic children's brain size becomes a bit larger than the normal brain size [9] [10]. Therefore, Magnetic Resonance Imaging (MRI) images can be a way of screening autism-related disorders. Another way can be analyzing the behavior, style of playing, and expression. These parameters can be effective for an AI-enabled model in the early detection of autism. Autistic individuals need constant monitoring, caring, therapy, and controlling. Therapy and special schools are very

Journal Pre-proof

Journal Pre-proof

Table 1: Number of autism diagnoses per 10000 children in developed countries [5]

Country	**Diagnosed Autism per 10000 Children**
Hong Kong	372
South Korea	263
USA	222
Japan	181
Ireland	153
Switzerland	145
Canada	106
Denmark	69
Singapore	67
Belgium	60
Estonia	60
Finland	54
Norway	51
Netherlands	48
Germany	38
China	23
Taiwan	5
Poland	3

costly, and these are not affordable for many families. IoT and AI-enabled devices have proved to be quite useful in this field. IoT devices and technologies such as cameras, sensors, virtual reality can be very handy in analyzing expression, monitoring, and behavior. Constant therapy can also be assured using sensors and AI-enabled digital devices. Visualization helps these children a lot in acquiring skills. Therefore, AI-enabled gaming can add a new dimension to this field. Sensor-based networks are also used to monitor their interaction, their response level, and to determine their progress. Robots have proved their usefulness in helping children to acquire necessary social skills. These devices and systems are quite affordable, perform well for autistic individuals, and capable of reducing human dependency on therapy and monitoring.

Current world is moving towards an IoT-based smart society, where AI-enabled devices would be everywhere. People will get assistance through it, which will reduce human intervention across a variety of sectors. A glimpse of this type of devices is already visible in hospitals, restaurants, roads, and so

Journal Pre-proof

Journal Pre-proof

many other places. It would be beneficial to design these devices for autistic individuals as well, since they can greatly reduce the demands of human assistance. These devices can assist them to become self-dependent and they can live by themselves through the assistance of this devices. This will assist a lot in incorporating them to the core part of the society which will ensure the smart device enabled society for all.

Some review works have been carried out, which cover the detection and intervention of autistic individuals. Noor H. A. et al. [11] reviewed 11 virtual game-based research works that could help autistic children. He covered games related to education, entertainment, health and simulation which can run on different devices such as computers, smartphones, and touch-sensitive displays. Knight et al. [12] evaluated research works related to technology-based intervention to acquire academic skills for autistic children. They reviewed 25 research works which were published between 1993 and 2012. Kaur et al. [13] analyzed 7 research works, where IoT has been used for autism detection. They selected publications based on human participation and quality of implementation. Moon et al. [14] analyzed the efficiency of ML algorithms in the diagnosis of autism from MRI images. They assessed 43 research works in this field and found that ML can be useful for autism detection. Hyde et al. [15] reviewed 45 papers on the use of supervised learning in autism, where they described the methods and processes of mining data mentioned in the selected articles. Jaliawala et al. [16] analyzed some research articles on the intervention process for autistic individuals. They discussed the existing research works based on computer vision, virtual reality, computer-aided systems, and AI.

Eman et al. [17] summarized 16 works that used ML classifiers for ASD detection. They discovered that most of the works used Support Vector Machine (SVM) [18] for classification purposes. Moon et al. [19] assessed the randomized control trials for mobile applications in the treatment of ASD. They ascertained that mobile applications can be effective in the treatment of ASD. Jouaiti et al. [20] analyzed research articles related to the use of the robot in motor deficits of autistic children. Robots are now using for the treatment of autistic individuals,

Journal Pre-proof

Journal Pre-proof

but the authors found that robots in motor rehabilitation therapy need more attention in the research community. Abirami et al. [21] summarized mobile application based research works conducted to help echolalia attacked autistic individuals. They showed how mobile application can help autistic people in acquiring necessary skills. Lorenzo et al. [22] reviewed research works that utilized immersive virtual reality in autism. They selected 12 research articles that dealt with social skills and the emotion recognition of autistic individuals. They analyzed the works on several criteria, such as research questions, features, used instruments, and so on. Song et al. [23] analyzed 13 research articles in the field of AI-based autism detection and screening. They have discussed different methods for ASD detection. They stated that a lot of challenges are there which are needed to be resolved before integrating AI in the healthcare sector. Table 2 provides an overview of the existing review works.

Table 2: Overview of the existing review works

Year	Ref.	Reviewed items	Topic of review
2012	[11]	11	Virtual games for autistic children
2013	[12]	25	Technology based intervention systems for acquiring academic skills
2015	[21]	6	Application of mobile application in echolalia attacked autism
2018	[22]	12	Application of virtual reality in autistic students
	[14]	43	Autism diagnosis from MRI Image using ML
	[15]	45	Application of supervised learning in autism
	[16]	28	AI-assisted systems for autism intervention
2019	[17]	16	ML classifiers in autism detection
	[23]	13	AI in autism assessment
	[20]		Application of Robot in motor deficits of autistic children
	[19]	7	Efficacy of mobile application in autism therapy trials
2020	[13]		IoT in autism detection

For this work, journal and conference papers related to the application of AI, ML, and IoT in autism were searched in renowned search engines, and 125 research articles were collected. After removing duplicates, 82 articles were there for review. After reviewing the abstract, 16 articles were excluded as they were not related to autism detection, monitoring, intervention, or assistance. Then

Journal Pre-proof

Journal Pre-proof

66 research articles were assessed, and 8 articles were found as review articles or thesis papers. After completing all the selection procedures, 58 research articles were finally selected for review. Among them, 20 articles were related to autism intervention, monitoring, and assistance, and 38 articles were related to autism detection. To the best knowledge of the authors, no review articles have been published which have described the AI and IoT based autism screening and management methods together. Figure 1 illustrates the research article selection process.

Figure 2(a) represents keywords of the selected articles which illustrates the overall picture of all the reviewed articles. Figure 2(b) shows the distribution of research articles by topic in a pie diagram. Most of the articles described autism detection process. Figure 2(c) provides a yearly distribution of selected articles. Most of the reviewed articles were published between 2017 and 2020.

The key contributions of this paper are given below:

- Thoroughly reviewed the efficacy of AI and IoT in screening and managing autism.
- Discussed the integration of smart city facilities for autistic people.
- Challenges in autism screening and management have been discussed.
- Research scopes in this field have been pointed out and described.

The rest of the paper is organized in the following structure: Section 2 describes the most used AI and ML algorithms in autism. Section 3 illustrates the most used smart sensors and devices. Section 4 describes the evaluation metrics. Section 5 outlines the research work in autism detection. An overview of the research work in therapy and monitoring of autistic people is provided in section 6. Autism in smart city is discussed in section 7. Section 8 describes some challenges and research scopes for further research and provides some recommendations. The paper is concluded with a summary in section 9.

Journal Pre-proof

Journal Pre-proof

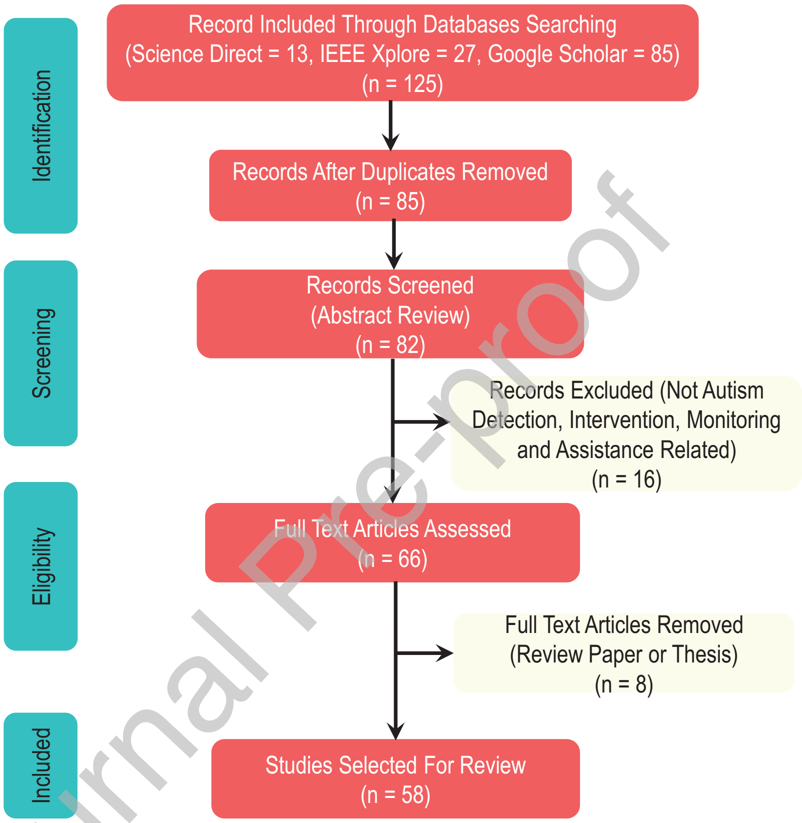


Figure 1: Prisma diagram of the article selection process followed in this work. The search string used in this work- (Autism OR Autistic OR ASD) AND (AI OR Artificial Intelligence OR IOT OR Internet of Things OR "ML" OR "Machine Learning") AND ("Classification" OR "Detection" OR "Screening" OR "Diagnosis" OR "Therapy" OR "Intervention" OR "Teaching" OR "Monitoring" OR "Assistance" OR "Helping"). 125 articles were collected using this search string and 58 papers were finally selected for review. The rest of the papers were removed due to duplication or was beyond the scope of this review.

Journal Pre-proof

Journal Pre-proof

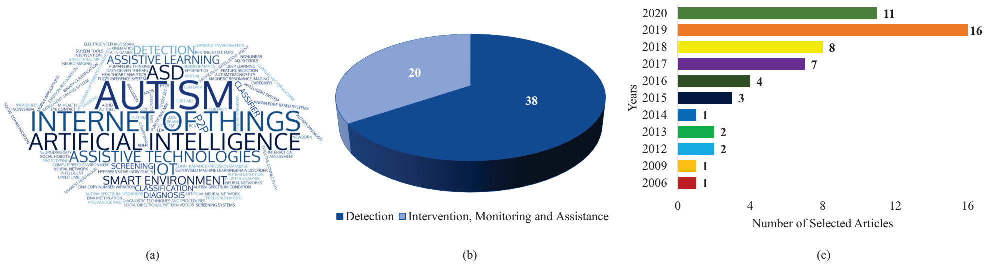


Figure 2: (a) Wordcloud generated from the keyword of the selected articles which indicates the focus of the reviewed articles; (b) Distribution of the selected articles by topic. Most of the reviewed articles were focused on autism detection. (c) Year-wise distribution of the selected articles. It is showing an increment of research interest in the field of autism using AI, ML and IoT.

2. AI and ML Algorithms

Machine Learning and deep learning can be very useful in detection [24, 25, 26, 27], classification [28, 29], pattern recognition [30, 31, 32, 33, 34, 35] and prediction applications [36, 37, 38]. Several AI and ML algorithms have been used in autism detection and intervention. Some of these algorithms have been discussed in this section.

2.1. Nave Bayes (NB)

NB [39] is an ML classifier that is based on the Bayesian theorem. It has the capability of outperforming sophisticated classifiers in some cases of classification problems. In the NB algorithm, it is taken into consideration that features will contribute independently to the probability. The Bayesian formula is defined using Eq. (1) and Eq. (2).

$$P(c \mid x) = \frac{P(x \mid c) \times P(c)}{P(x)} \tag{1}$$

$$P(c \mid x) = P(x_1 \mid c) \times P(x_2 \mid c) .... \times P(x_n \mid c) \times P(c) \tag{2}$$

Here, c is the target class, x_1, x_2,.....,x_n. are the attributes of predictors. $P(c|x)$ is the probability of c provided that x is given, $P(x|c)$ is the likelihood

Journal Pre-proof

Journal Pre-proof

of the predictor given class, probability of class is $P(c)$, and probability of predictor is $P(x)$. Therefore, each feature is contributing independently to the classification result. NB is fast, efficient, and can handle missing values. It is found quite efficient in various classification [40, 41, 42] and detection [43, 44] tasks.

2.2. Decision Tree (DT)

DT [45] is a flow chart shaped architecture that splits the sets into smaller subsets according to the attribute values. Each internal node performs a test based on an attribute and proceeds further. This process is performed recursively, which is called recursive partitioning. The leaf nodes provide a class label. It requires less computing power, handles different kinds of variables, and capable of understanding rules. This algorithm Some variations of DT such as ID3 [46], J48 [47], CART [46] have been used in autism classification. Figure 3(a) shows a sample DT for autism detection. Each branch provides a subset, where the leave denotes the class label as ASD or No ASD.

2.3. Support Vector Machine (SVM)

SVM [48] is a classification algorithm that discriminates 2 classes by creating a hyperplane between data points. It tries to draw a hyperplane in a way that maximum distance establishes between the 2 classes. It is capable of working with both linear and nonlinear data. In the case of nonlinear data, it takes itself to a higher dimension in which it can draw a hyperplane to classify classes which is called kernel trick. SVM is capable of multiclass classification by using one vs. all techniques. SVM is computationally expensive, and provides excellent accuracy in different classification tasks [49][50]. It is mostly used for autism detection from the MRI image [51] or behavioral [43] data. Figure 3(b) illustrates the classification procedure of SVM.

2.4. Logistic Regression (LR)

LR is an ML algorithm which provides value in the range of 0 and 1. It is handy in binary classification tasks [52, 53]. It uses the logistic function to

Journal Pre-proof

represent data where a decision boundary is drawn between classes to provide a prediction. Figure 3(e) shows the curve of the logistic function. Mathematical expression of the logistic function is provided in Eq. (3).

$$g(z) = \frac{1}{1 + e^{-z}} \tag{3}$$

Here, $g(z)$ is the logistic function for any real number denoted by z. The implementation of LR is simple, and it requires low computational cost. It is not efficient in multiclass classification. It has been found to be useful for detection of ASD [54].

2.5. K Nearest Neighbor (KNN)

KNN [55] is a non-parametric classifier which functions based on feature similarity. It is simple and widely used for pattern recognition [56], multi-label classification [57], and so on. Here, K represents the selected number of elements in a cluster. The cluster is determined based on distances between data points. At first, distance is measured between the data points using different distance functions, such as Euclidean distance [58], Minkowski distance, and so on. The mathematical expression of distance is given in Eq. (4).

$$d(x, y) = (\sum_{i=1}^{n} (|x_i - y_i|)^p)^{\frac{1}{p}} \tag{4}$$

Here, x and y are data points and $d(x, y)$ is the distance between them. If $p = 1$, then it denotes the equation of Manhattan distance. In case of $p = 2$, it provides the formula of Euclidean distance. KNNs performance is mainly dependent on these distance functions [59]. These distances are being sorted to find out clusters and classes. This classifier performs well when the number of variable is low. KNN is quite useful in classification and recognition tasks [60].

2.6. Random Forest (RF)

RF is an ensemble learning method based classifier where multiple DT are constructed [61]. Each DT provides a classification result, and RF works by

Journal Pre-proof

Journal Pre-proof

combining these outcomes. It uses feature bagging where trees are being trained with subsets of the total dataset, which is selected randomly. It eliminates the effect of strong variables. Figure 3(c) illustrates the RF process where multiple DT are providing their prediction, and the outcome provided by the majority of trees is selected as the prediction by the RF. It has less overfitting problem as it produces prediction by averaging the outcome of multiple trees. RF is computationally costly and needs a larger time for training. RF is widely used in various classification and regression tasks [62, 63, 64]. It has been used for autism detection [65, 66] and emotion detection [67] in many research works.

2.7. Linear Discriminant Analysis (LDA)

LDA [68] is a technique for separating 2 classes and reducing dimensionality. It models the attributes in a lower dimension space from a higher dimension. It creates a new axis for maximizing the distance between means of the classes and reducing intra-class variance. In this way, it separates the data points of the classes by generating a new axis. The efficiency of this algorithm mainly depends on the mean value of the attributes. It can be used in recognition tasks [69].

2.8. Convolutional Neural Network (CNN)

CNN [70] is one of the most popular deep learning (DL) architecture for image classification [71, 72, 73], estimation [74, 75] and pattern recognition [76]. It can extract higher-level features from data and capable of providing a very high accuracy. It is comprised of input, convolution, pulling, and fully connected layer. The input layer takes an image or data as input to the model. The convolutional layer is mainly used for feature extraction, where it extracts feature maps. Pooling layers are used for reducing the spatial dimension of feature maps. Different kinds of pooling operations, such as max-pooling, min-pooling, and so on can be performed. The extracted feature set is given input to the dense layers, which provide the probability of the classes. Dense layers find out the pattern from the extracted feature set and provide a class label.

Journal Pre-proof

CNN is computationally expensive and requires a large dataset for training. Overfitting is a problem in CNN which can be managed by introducing dropout layers in the CNN architecture. Sometimes, batch normalization layers are used for enhancing performance. Figure 3(d) illustrates the CNN architecture. CNN has been demonstrated to be useful for ASD detection [44] and facial expression recognition of autism children [77] in many research works.

2.9. Artificial Neural Network (ANN)

ANN was designed in such a way that it works similarly to a human brain. It consists of neurons that are connected, and these connections have some weights and biases. Training an ANN model means tuning the weights and biases to produce the best prediction output. An ANN has mainly 3 layers: an input layer that takes data as input, hidden layers for feature extraction, and an output layer for providing classification result. Each layer has some activation functions that take inputs and biases of the previous layers, calculate the weighted summation of them, and reproduce value within the desired range. In this way, data move forward, and the output layer provides the classification result. In each iteration, an error is calculated, and the backpropagation algorithm [78] is followed to minimize the error by adjusting weights and biases. The learning rate becomes multiplied with these values and is subtracted from weights. Figure 3(f) illustrates the basic structure of ANN. ANN is capable of providing outstanding accuracy in classification tasks [79, 80] and can also be used for various kind of applications [28, 29, 81, 82].

2.10. Auto-encoder

Auto-encoder [83] is a type of neural network (NN) which consists of an encoder and a decoder and tries to generate the input as a form of output after an encoding and decoding process. It creates a bottleneck where input gets modified by the encoder NN, and the decoder tries to regenerate the input from the encoder's output. A loss function is calculated that defines the difference between actual input and generated input. The architecture tries to adjust its

Journal Pre-proof

weights and biases by adopting the backpropagation algorithm and reduces the loss. It is an unsupervised U-shaped architecture that is mainly used to provide a compressed representation of data. It is also used for feature extraction purposes [84]. Auto-encoder is being used in many classification and recognition tasks [85]. Figure 3(g) illustrates the basic architecture of auto-encoder.

3. Sensor and Smart Devices

IoT is dependent on smart devices and sensors. A lot of sensors are now being integrated in devices to analyze activity, motion, and state of the environment. Various sensors and devices have been widely used in autism related research works. This section covers description of popular sensors and devices.

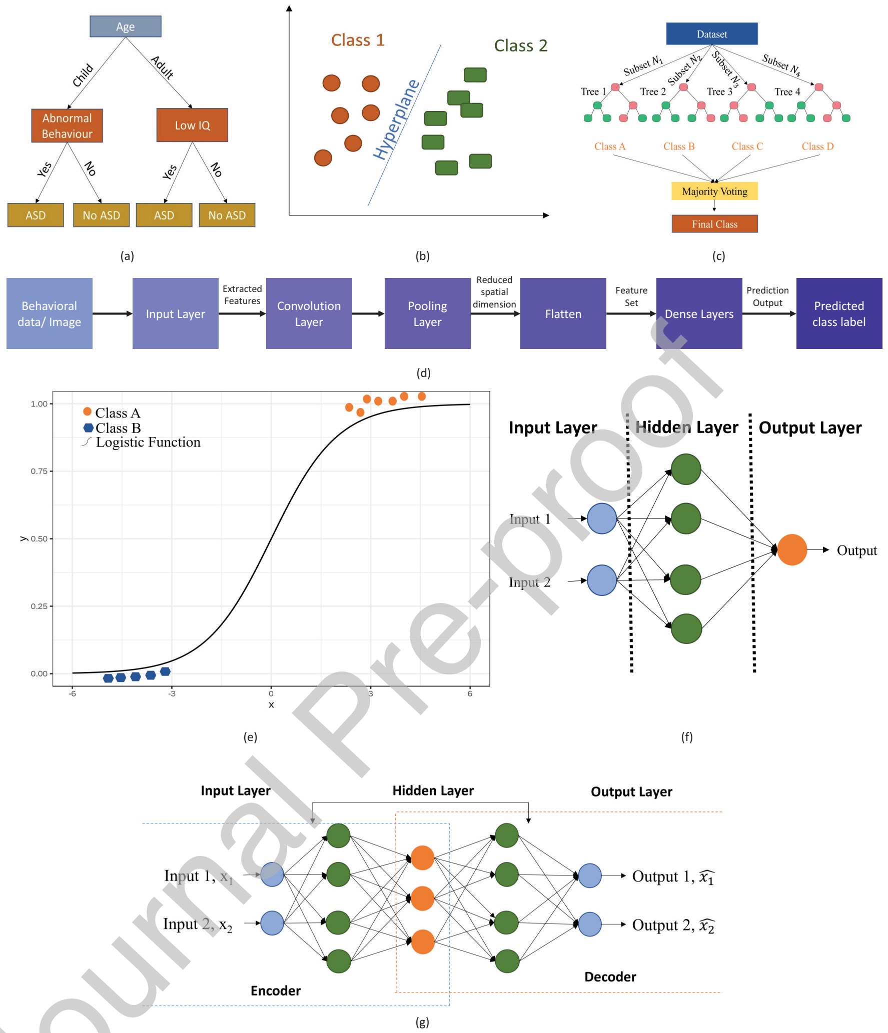
3.1. Accelerometer

An accelerometer is mainly used for measuring vibration or acceleration. It provides a value based on the force exerted by the acceleration of a thing, which creates squeezes on piezoelectric material to generate an electric charge. It can provide values in 3 coordinates that detect the position and direction of a device. It can be used for fall detection [86, 87], activity recognition [88], movement analysis [89], motion analysis [90], and so on. In autism, it can be used for autistic children's movement detection, activity recognition, and also in various monitoring tasks [91, 92, 93].

3.2. Gyroscope

Gyroscope is mainly used for determining the orientation of an object or person. It uses the earth's gravity to detect orientation. A torque is applied on the rotating disc of the gyroscope along the perpendicular direction of the sensor to get precision. It is widely used in mobile devices, activity recognition [94], elderly monitoring [95], and so on. Gyroscope has been used for monitoring and tracking the movement of autistic individuals in several researches.

Journal Pre-proof



Journal Pre-proof

Figure 3: (a) A simple example of a DT for ASD diagnosis; (b) Classification procedure of SVM. It tries to create a hyperplane between 2 classes; (c) Decision-making process of RF. Each DT provides its prediction result to provide the final predicted class label; (d) A simple CNN architecture. It consists of a convolutional layer to extract feature, pooling layer to reduce dimensionality, dense layer to provide a predicted class label; (e) A generated curve for logistic function; (f) A simple ANN architecture consists of an input layer, a hidden layer, and an output layer; (g) An auto-encoder architecture. It is comprised of an encoder and decoder. The encoder takes input and converts it to a smaller tensor where the decoder takes the smaller tensor as input and tries to regenerate the input data.

3.3. Microsoft Kinect

Microsoft Kinect is a device that has a set of sensors such as camera, depth sensor, microphone, and so on. It is used in different activity recognition, monitoring, speech recognition related research works [96, 97, 98, 99]. RGB camera in Kinect is used for capturing video. Many researchers used cameras in autism-related research for autism detection, monitoring, emotion recognition [100], and so on. The microphone is also an important device for emotion recognition from voice signals. Speech signals have been analyzed in autistic interventions, and detection related research works [101].

3.4. Temperature and Humidity Sensor

Temperature and humidity sensors are used to get an idea of the surrounding environment of a subject. It can detect sudden changes in the temperature of an area. It is used in temperature-controlled automated systems [102], body temperature monitoring, and so on related works. It can be used for making the environment comfortable for autistic children and in the health monitoring of autistic individuals [100].

3.5. Radio Frequency Identification (RFID)

RFID tags are mostly used for object tracking [103]. It works by using radio frequency. It consists of a small radio wave receiver and sender. An RFID reader is used to detect RFID tags. If an RFID tag is within an area covered by the RFID reader, the RFID tag transmits a signal to the RFID reader. It can be used in teaching objects [104], and also in daily applications [105] for autistic people.

3.6. Smartwatch

Smartwatch is a wearable device that is comprised of heart rate monitor sensor, blood pressure measuring sensor, pedometer, Global Positioning System (GPS), and so on. Smart watch is now being used for several monitoring tasks.

Journal Pre-proof

Journal Pre-proof

For instance, heart rate monitoring is an essential task for ensuring health condition monitoring [106, 107]. GPS is very handy for locating the position of a person. Blood pressure measurement is essential in assessing health conditions [108]. Smartwatch is also useful in measuring the physical activity level [109]. A smartwatch or smartwatch-like wearable device can ensure proper health monitoring and tracking of autistic children.

4. Evaluation Metrics

Evaluation metric is a way of measuring efficiency of a proposed method. In this section, several evaluation metrics and formula for obtaining these are described.

4.1. True Positive Values (TP)

In autism detection, the number of instances in which the architecture predicted autism matches the actual autism samples are said to be true positive values.

4.2. True Negative Values (TN)

A sample can be counted as true negative value if the model classifies an instance as negative sample and it is actually not a sample of autism.

4.3. False Positive Values (FP)

It means the number of occurrences the model classified an instance as autism, but it was not denoted as autism in the real dataset.

4.4. False Negative Values (FN)

It means the number of occurrences the model could not classify an instance as autism, but it was an autistic instance in the real dataset.

Journal Pre-proof

4.5. Sensitivity

Sensitivity means the rate of correct classification of positive instances. It can be calculated by Eq. (5).

$$Sensitivity = \frac{TP}{TP + FN} \tag{5}$$

4.6. Specificity

It means the negative samples that were correctly classified by the proposed architecture. It is obtained by using Eq. (6).

$$Specificity = \frac{TN}{TN + FP} \tag{6}$$

4.7. Accuracy

Accuracy denotes the percentage of correctly classified samples from the total number of samples. It is computed using Eq. (7).

$$Accuracy = \frac{TP + TN}{TP + FP + FN + TN} \tag{7}$$

5. AI, ML and IoT for Autism Detection

Autistic individuals act quite differently than ordinary people. Their expression, behavior, learning capability, attitude, IQ score and MRI images are very useful parameters for diagnosing autism. Most researchers used different ML and DL algorithms such as SVM, LR, NB, ANN, KNN, and so on. and DL algorithms such as CNN, Recurrent Neural Network (RNN), and so on for diagnosing autism. Apart from these algorithms, they have used different image processing approaches for feature extraction and adopted different rule-based methods such as Fuzzy logic for classifying ASD.

Researchers have considered brain images, behavior, activity, speech, and so on. as a feature for detection autism. Several datasets have been created based on these features. Autism Brain Imaging Data Exchange (ABIDE) I [110] is a resting fMRI dataset that contains anatomical and phenotypic data. This dataset has a total of 1112 instances (539 ASD, 573 No ASD). ABIDE

Journal Pre-proof

Journal Pre-proof

II dataset is an upgraded version of the ABIDE I that contains data of brain connections. It has 1114 samples (521 ASD, 593 No ASD). Autism Spectrum Quotient (AQ-10) [111] is a screening tool in which a set of 10 questions are asked to the patient and caregivers. It has a total of 21 attributes, including the class label. The questions are set according to the age of the subject. Autism Diagnostic Observation Schedule (ADOS) [112] is an autism screening tool that consists of a set of tasks to be performed by the subject. The examiner judges the subjects' performance and finds out the difficulty of the subject in social and communication behaviors. There are 4 modules in the ADOS screening test. The module and task are selected based on the skill of the subject. The Autism Diagnostic Interview-Revised (ADI-R) is a questionnaire-based screening tool where an entire set of 93 questions can be asked to the caregivers. Autism screening is dependent on the answers to these questions. The questions are related to social interaction, communication, and repetitive behavior of the subject. Table 3 provides an overview of the most used screening tools for autism detection.

Table 3: Overview of the autism screening tools

Screening Tool	Data Type	Age Group	Instances/ Datasets
ABIDE I	fMRI	7-64 years	1112 instances (539 ASD, 573 No ASD)
ABIDE II		5-64 years	1114 instances (521 ASD, 593 No ASD)
AQ-10 (Child)	Questionnaire	4-11 years	292 instances, 21 features
AQ-10 (Adolescent)		12-15 years	104 instances, 21 features
AQ-10 (Adult)		Age > 15 years	704 instances, 21 features
ADI-R		Mental age > 2 years	No Specific dataset, 93 questions
ADOS	Tasks	Age > 12 months	No Specific dataset

In this section, various AI, ML and IoT based research works for autism detection using different screening tools have been discussed. Figure 4(a) shows the most used classifiers for autism detection. Figure 4(b) shows the frequency of screening tools mentioned in autism research articles. Figure 4(c) shows the basic steps for autism detection.

Journal Pre-proof

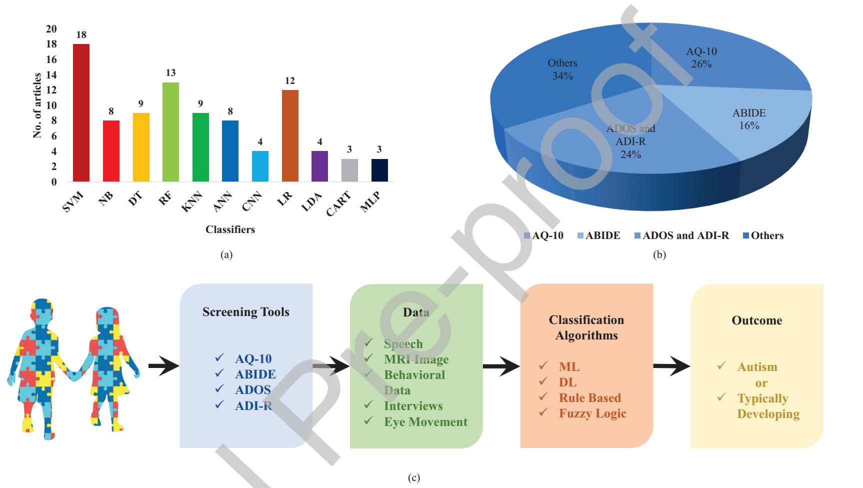


Figure 4: (a) Most used classifiers for detecting autism. SVM was used in 18 researches out of 38 research works for detecting autism; (b) Most popular Autism screening tools. AQ-10 was used in 26% research works. Apart from these, eye movement, behavioral data was used for autism detection by mane researchers; (c) Process for detecting autism. Different form of data is collected from autistic individuals by using different screening methods. This features are used further for autism detection by different classifiers.

5.1. Research Works on Autism Detection using AQ-10 Screening Tool

AQ-10 questionnaire is different for child, adolescent and adult. Subject areas from which questionnaire has been created is provided in Table 4. Many researchers have used these questions of the AQ-10 screening tool to create a feature set for autism detection. After that, several ML and DL algorithms were applied to classify the instances. Table 5 provides an overview of this kind of research works.

Table 4: Considered subject areas during creating questionnaires of AQ-10 [111]

Child	Adolescent	Adult
Notices small sounds when others do not	Notices patterns in things all the time	Notices small sounds when others do not
Difficulty in tracking the small details	Difficulty in tracking the small details	Difficulty in tracking the small details
Difficulty in Keeping track of several different people's conversation	Difficulty in Keeping track of several different people's conversation	Difficulty in multitasking
Can switch between different activities or not	Can switch back to previous activity in case of an interruption or not	Can switch back to previous activity in case of an interruption or not
Difficulty in carrying on conversations	Difficulty in carrying on conversations	Difficulty in understanding 'read between the lines' during conversations
Difficulty in social chit-chat	Difficulty in social chit-chat	Understands partner's mood during conversations
Difficulty in understanding characters feelings or intentions after reading a story	Enjoyed playing games involving pretending with other children when s/he was younger	Difficulty in understanding characters feelings or intentions after reading a story
Enjoy playing games involving pretending with other children	Difficulty in imagining what it would be like to be someone else	Likes collecting information of things or not
Can understand someone's feeling or thinking just by looking at their face	Difficulty in dealing with social situations	Can understand someone's feeling or thinking just by looking at their face
Difficulty in making friends	Difficulty in making friends	Difficulty in understanding peoples intentions

Journal Pre-proof

5.1.1. Overview

Peral et al. [47] proposed an autism diagnosis architecture based on data integration, analysis, ML, and data transformation. They at first collected data from all possible sources and used ontologies to integrate all the data sources.

Journal Pre-proof

They performed ontology-based semantic tagging, core ontology selection, and ontology mapping. Then different ML algorithms were implemented on the data. They collected 3 AQ-10 datasets which contain data of children, adolescence, and adult. Each dataset had 20 features. They integrated these 3 datasets using new variables. Wordnet was the core ontology that defines the noun, adjective, and verb. They performed ontology mapping and then performed feature reduction, which removed 8 unnecessary features from the dataset. Then ML algorithms such as DT, SVM, NB, Adaboost, ANN, Attribute selected classifiers were applied to it. It reduced dimensionality based on train data and selected SVM as best performing classifier. This method achieved more than 97% accuracy, 96% sensitivity, and 98% specificity in the complete dataset. They generated a dashboard based on these results.

Omar et al. [46] proposed an RF-CART and RF-ID3 based approach to detect autism in children, adolescents, and adults. They collected the AQ-10 dataset and also created a dataset that contained ten questions. In these questions, the user scored 0 or 1 according to their answers. After that, the dataset was cleaned, null values and irrelevant attributes were removed. AQ-10 dataset had around 958 instances, and their self-created dataset contained 250 records. Then the prediction model was created. At first, the trees were built based on the best features. A defined number of ID3 trees and CART trees were created where ID3 used entropy, and CART used Gini impurity to calculate the information gain. ID3 was merged with CART to enhance randomness and reducing overfitting. After that, voting was done by the DTs for each test instance, and the majority of votes classified an instance as autistic or not. The proposed methods achieved an accuracy of 92.26%, 93.78%, and 97.10% in the child, adolescence, and adult dataset of AQ-10. The sensitivity achieved by the proposed model was 96.52%, 98.60%, and 97.07% in child, adolescence, and adult dataset of AQ-10 consecutively. The proposed model performed quite well in their self made dataset by achieving 77.26% in the child set, 79.78% in the adolescence set, and 85.10% in the adult set.

Erkan et al. [66] proposed an ML-based approach for autism detection. They

Journal Pre-proof

Table 5: Overview of the reviewed research works related to autism detection by AQ-10 screening tools and ML, AI and IoT

Cite	Age Group	Algorithms / Models Used	Results (Highest Accuracy)
[47]	Child, Adolescenence, Adult	SVM, NB, ANN, J48 DT, RF, Adaboost	97% by SVM
[46]		RF-CART and RF-ID3	95.5% by RF-CART and RF-ID3
[66]		SVM, KNN, RF	100% by RF
[113]		RML	90.72% by RML
[44]		KNN, SVM, LR, ANN, NB, CNN	98.95% by CNN
[114]		DT, NB, KNN, Random Tree, DL	96% by DL
[115]		Adaboost, c5.0, GLMBoost, LDA, SVM, CART	97.80% by LDA
[116]	Adult	LDA, NB, CART, KNN, LR, SVM	72.2% by LDA
[117]		LR, RF, KNN	97.54% by LR
[118]	Child, Adult	LR, NB, AD tree, RF	100% by ADtree and LR

collected data from the UCI repository, which followed the AQ-10 screening tool. The dataset contained 1100 data combining 3 datasets for child, adult, and adolescence. The data were converted to numeric form before giving input to ML models. SVM, KNN, and RF were used for classification purposes. 5 testing scenarios were set up with ratios of 50:50, 60:40, 70:30, 80:20, and 90:10 for training and testing. RF achieved a perfect 100% accuracy in all the experiments and missing value conditions.

Thabtah et al. [113] proposed a Rule-based ML (RML) technique for autism detection using AQ-10 and Q-CHAT-10 screening tools. The data was collected through a mobile application. A total of 704 (515 No ASD, 189 ASD) cases were included in the dataset. The features were converted to binary attributes. A feature selection procedure was run to remove redundant features, and then rules were found out over it. Each rule had data coverage, and they were not overlapping with each other. After that, a classifier was used to evaluate the rule in order to predict the value of the class. They implemented several classifiers such as C4.5, CART, Adaboost, bagging, and so on to evaluate classification performance. The enhanced RML achieved an error rate of 5.6%, which is less than other classifiers. RML achieved more than 94.5% accuracy in the adult set, 87% accuracy in the adolescence set, and 90% accuracy in the child set.

Journal Pre-proof

Raj et al. [44] used ML and DL approach to detect autism. They used 3 publicly available datasets based on AQ-10 screening tools and contained 1100 instances (704 adult instances, 292 child instances, 104 adolescent instances) where each instance had 21 attributes. The dataset underwent several pre-processing tasks such as handling null value, removing outlier, data reduction, normalization, and so on. Then the dataset was divided into training and testing part at a ratio of 80:20. KNN, SVM, LR, ANN, NB, and CNN classifiers were used for detection purposes. In CNN, they used the ReLU activation function, Adam optimizer, 16 and 32 filters, and 50% dropouts. CNN achieved the highest accuracy in all 3 datasets. In the Adult dataset, CNN achieved 99.53% accuracy, 99.39% sensitivity, and 100% specificity. The proposed CNN architecture achieved 98.30% accuracy, 96.78% sensitivity, and 100% specificity in the dataset for children, and 96.88% accuracy, 93.35% sensitivity, and 100% specificity in autism diagnosis for adolescents.

Halibas et al. [114] compared different ML algorithms to analyze the models' performance based on precision, recall, and ROC. They have used the UCI dataset, which contains 292 children, 104 adolescence, and 704 adult sample. 16 out of the 21 attributes were used for this purpose. They compared DT, NB, KNN, random tree, and DL for finding the best performing model. DL and NB provided the best result (96.38% and 90.30% accuracy respectively), where random tree achieved the worst accuracy among the described models.

Akter et al. [115] evaluated the performance of different ML algorithms for different datasets. 2009 records from Kaggle and UCI database were used for training the models. They used 250 different classifiers for autism detection and compared their results. They replaced the missing values with the mean and converted the categorical features into numeric values in the pre-processing stage. Among the 250 algorithms, 80 algorithms performed well. They selected 9 of them for the final comparison. They used feature transformation by log, z-score, and sine conversion. For toddlers data, AdaBoost and SVM achieved 100% accuracy. For children dataset, LDA and PDA achieved 95% accuracy. Adolescence data was well classified by C5.0, LDA, and PDA algorithm. AdaBoost produced 98.36% accuracy for the adult dataset.

ML algorithms are suitable for diagnosing ASD as they are capable of achieving a very high accuracy in classification and detection tasks. Tyagi et al. [116] compared different ML algorithms based on their performances in the diagnosis of autism. LDA, regression tree (CART), KNN, LR, SVM were used for this comparison. They utilized the UCI dataset for this purpose, which had 702 instances. Among the 702 samples, 189 were ASD patients, and the rest were the data of normal person. The data was split at a ratio of 70:30 for training and testing purposes. The LDA model performed the best with 72.2% accuracy, and LR was able to achieve 72.02% accuracy.

Abdullah et al. [117] used ML classifiers and feature selection techniques to detect ASD from AQ-10. They collected 704 records (189 ASD, 515 No ASD), where each record contained 20 features and 1 class value. Then null values were removed which reduces the number of instances in the dataset. Lasso and Chi-squared methods were applied for feature selection. They selected several alpha values and performed gridsearchCV, where the c value was set to 10. They built 5 LR models, 6 RF, and 5 KNN models. The LR (13 features) performed the best by achieving 97.54% accuracy, 100% sensitivity, and 96.59% specificity.

Based on the gold standard autism diagnosis, a great deal of time is needed. To reduce this time, automate the process, and enhance the prediction accuracy, Elavarasi et al. [118] proposed an ML based model. They used 2 datasets, which are AQ-10-children (292 instances), and AQ-10-Adult (104 instances). The questions were framed using the Q-CHAT-10 method. In the pre-processing stage, missing values were removed, and normalization was performed. For both of the datasets, they tried LR, NB, ADTree, and RF. The ADTree and LR models achieved 100% accuracy, 100% sensitivity, and 100% specificity.

5.1.2. Performance Comparison

Most of the research works successfully achieved very high accuracy and sensitivity in autism detection using the AQ-10 screening tool and ML algorithms. Elavarashi et al. [118] acquired 100% accuracy, 100% sensitivity, and 100%

Journal Pre-proof

specificity using LR in detecting autism that is the highest using the AQ-10 screening tool. They did not deal with the adolescent dataset. Erkan et al. [66] also achieved 100% accuracy and sensitivity using RF, but they used all 3 datasets: adult, adolescent, and child. Raj et al. [44] found 98.95% accuracy and 100% sensitivity using CNN. Akter et al. [115] also achieved a very high 97.80% accuracy and 97.94% sensitivity by using LDA. Abdullah et al. [117] and Peral et al. [47] also acquired quite good accuracy (97.54% , 97%) and sensitivity (100%,96%) in the case of autism detection. Figure 5 shows a comparison of the reviewed research works based on accuracy, sensitivity, and specificity.

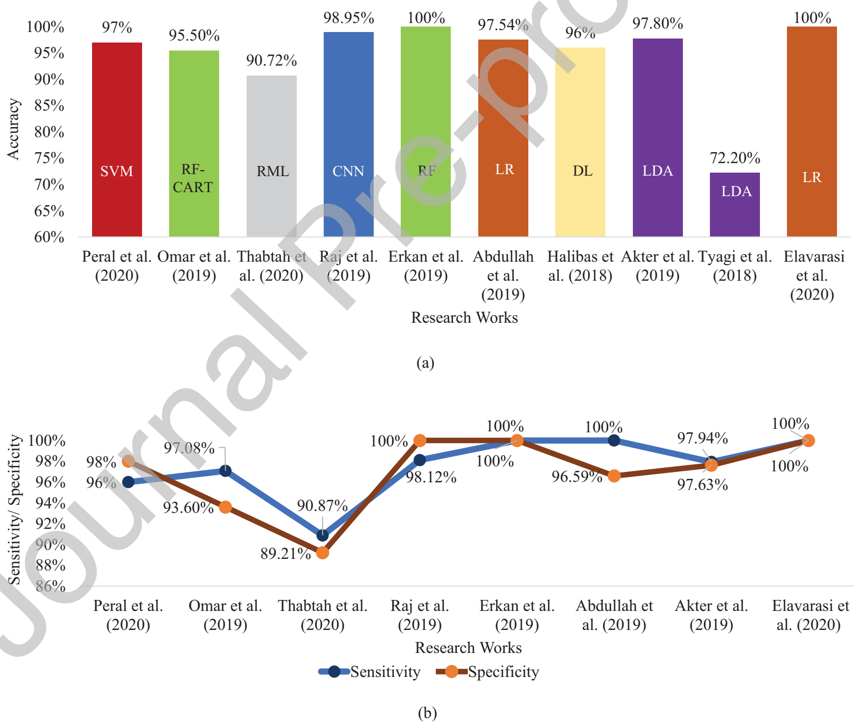


Figure 5: (a) Performance comparison of the selected research works that used AQ-10 screening tool based on accuracy. Highest accuracy achieved by the researchers was 100%; (b) Performance comparison of the selected research works that used AQ-10 screening tool based on sensitivity and specificity. Highest sensitivity achieved by the researchers was 100%.

Journal Pre-proof

5.2. Research Works on Autism Detection using ABIDE Screening Tool

ABIDE I and II contain fMRI images and features of the MRI images.fMRI images has been shown to be effective in autism screening, as the brain structure of autistic and typically developing individuals differs a bit. Table 6 provides an overview of the research works in autism detection using ABIDE screening tool.

5.2.1. Overview

Thomas [119] et al. proposed an image processing and ANN-based method for diagnosing ASD from MRI images. They used the ABIDE dataset for this purpose. At first structural MRI images were given input which went through a series of image pre-processing stages such as geometrical transformation, pixel brightness transformation, extracting knowledge, and so on. After that, a non-linear median filtering technique was imposed for noise reduction. Then 20 features were extracted using Gray-Level Co-Occurrence Matrix (GLCM). The brain area was calculated, merged with previous features, and then it was provided as input to ANN, which distinguished between autistic and normal brain areas because the brain area of an autistic person should be larger than that of a normal person. Functional MRI images also went through image pre-processing and image-quality enhancement stages. After that, segmentation was performed to find meaningful features, and images were sliced into parts. Extracted features went through an ANN, which was trained and tested for autism detection.

Sharif et al. [120] proposed ML and VGG16 based architectures for detecting ASD from an MRI image. They used the ABIDE dataset containing images of 1,112 subjects and also collected corpus callosum and intracranial brain volume data from the T1 weighted MRI scan. The proposed framework was based on the extracted weight from the data. These data were calculates using different softwares such as Yuki, fsl, itksnap, and brainwash, where 12 features were extracted from the data. They experimented with several feature selection methods such as information gain, information gain ratio, chi-square error, symmetrical uncertainty, and so on. They implemented ML algorithms such as

Journal Pre-proof

Journal Pre-proof

LDA, RF (10 trees), SVM (RBF kernel), MLP, and KNN, where they found out the highest 55.93% accuracy using LDA after 5-fold-cross validation and feature selection. After that, they applied the VGG16 model for classification purpose and achieved 66% accuracy for autism detection.

Table 6: Overview of the reviewed research works related to autism detection by ABIDE screening tools and ML, AI and IoT

Cite	Age Group	Algorithms / Models Used	Results (Highest Accuracy)
[119]	Not Specified	ANN, GLCM	Only method proposed
[120]		LDA, RF, SVM, MLP, KNN, VGG16	66% by VGG16
[54]	Child, Adult	DT, RF, SVM, KNN, NN, LR	62% by NN
[51]		SVM, Auto-encoder, MLP	82% by MLP
[121]	All ages	ANN, RNN, CNN	75.54% by ANN
[122]	Child	MLP, RF, SVM, NB	61.1% by SVM

Parikh et al. [54] analyzed the performance of ML and DL classifiers to detect ASD from personal characteristics data which were collected from the ABIDE dataset. They used 6 features that are age, sex, handedness, Full-scale IQ, verbal IQ, and Performance IQ. They selected several ML and DL algorithms such as DT, RF, SVM, KNN, NN, LR, and so on. NN achieved 62% accuracy, 53.3% sensitivity, 71.2% specificity, and 0.646 AUC, which was the best result compared to the performance of other models.

Eslami et al. [51] proposed 2 DL and ML-based architecture named ASD-Diagnet and Auto-ASD-network for ASD diagnosis from fMRI data. They collected data from ABIDE datasets and performed feature engineering to enhance the number of samples and generated synthetic samples. They also performed some feature engineering where they divided brain data into 200 regions. A 19,900 pairwise correlation was used as a feature set in their proposed method. In ASD-Diagnet, at first, feature set was reduced to half by taking 1/4th highest and 1/4th lowest correlation. Then data augmentation was done on it that was given input to an auto-encoder to find more features. The auto-encoder generally uses a bottleneck to extract more features, which were given input to a single layer perceptron for classification. In Auto-ASD-network, MLP was

Journal Pre-proof

used in place of auto-encoder, and SVM was used for classification purpose. The parameters of SVM were tuned to find out the best performance. These models were tested on several ABIDE datasets, where ASD-Diagnet achieved the highest 82% accuracy in autism detection. They found 79.1% sensitivity and 83.3% specificity in that case.

Byeon [121] et al. adopted an ANN-based approach for classifying ASD from functional MRI image, where they utilized the ABIDE I dataset. They merged FMRI data and phenotypic information such as age, IQ, and so on. They removed low-quality images and also the images without phenotypic information. The FMRI images went through a normalization process and noise correction method using 24 motion nuisance signal regression. Then it was filtered, and the region of interests were calculated using Brain Netome atlas (BNA). The signal was once again normalized by subtracting mean and dividing by standard deviation. The proposed ANN model considered mean time course data and time points as input. It first went through a spatial dimension reduction layer to extract semantic features. This layer contained a 1D convolution with 20 filters, which converted the feature map to 20×146. Then 3 1D-convolutional layers were merged that had different kernel sizes, and it also contained a max-pooling layer for dimensionality reduction. The feature converted to 96×44. A 2-layered GRU RNN was used for calculating the hidden state. All hidden features were combined using the second RNN layer. 6 types of phenotypic data were processed using 2 fully connected layers. These layers provided 15 features, and it was merged with 32 RNN features. 2 more fully connected layers were considered for classification purposes. All the convolutional layers used Leaky ReLu activation function apart from the fully connected layers that used ReLU activation function. The optimizer was Adam, the learning rate was set to 0.01, and the model was trained with 200 epochs. The proposed architecture acquired 75.54% accuracy, 63.45% sensitivity, and 84.33% specificity in ASD classification, which was a huge improvement of the previous works.

Tejwani et al. [122] used ML algorithms to classify autism from the functional variability of brain regions. They used the ABIDE-I dataset from where

Journal Pre-proof

Journal Pre-proof

they selected 147 ASD subjects and 146 healthy subjects. They extracted resting-state fMRI images, calculated node variability and strength. They created 2 different feature sets, where all 200 node features and nodes showed variability < 0.9. They took the same proportion of data from each site. They trained MLP, RF, SVM, NB, and they achieved 61.1% accuracy, 61.8% sensitivity, and 60% specificity using SVM classifier and node strength as the feature set.

5.2.2. Performance Comparison

Autism detection using fMRI images could not achieve better accuracy than approaches using behavioral data. Eslami et al. [51] achieved the highest accuracy (82%) and sensitivity (79.10%) by adopting an MLP classifier among the research works performed using the ABIDE screening tools . Byeon et al. [121] achieved an accuracy of 75.54% where sensitivity was 63.4%, and specificity was 84.33% by using RNN. Sharif et al. [120] achieved an accuracy of 66% using state-of-the-art CNN architecture. Figure 6 shows a comparison of the reviewed research works based on accuracy, sensitivity, and specificity.

Journal Pre-proof

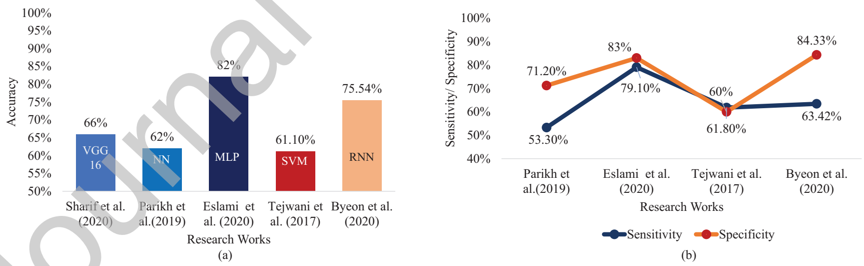


Figure 6: (a) Performance comparison of the selected research works that used ABIDE screening tool based on accuracy. Highest accuracy achieved by the researchers was 82%; (b) Performance comparison of the selected research works that used ABIDE screening tool based on sensitivity and specificity. Highest sensitivity achieved by the researchers was 79.1%, where highest specificity was 84.33%.

Journal Pre-proof

5.3. Research Works on Autism Detection using ADOS and ADI-R Screening Tool

Several research works have been carried out for diagnosing autism from different videos of activities and behavioral data. In ADOS, clinicians detect autism from the video of playing or performing tasks. Clinicians ask several questions to the caregivers for detecting autism in the ASD-R screening process. Several researches have been carried out to detect autism from ADOS and ADI-R screening tool data using AI, ML, and IoT. Table 7 describes the considered areas of ADOS and ADI-R dataset. Table 8 provides an overview of this kind of research works.

Table 7: Considered subject areas of ADOS and ADI-R

ADOS (Module-1)	ADI-R
Frequency of vocalization directed to others	Age discrepancy became apparent
Gestures	Motor (crawling and walking) milestones
Pointing	Early Symptoms
Facial expressions directed to others	Loss of language
Showing	Qualitative abnormalities in communication
Unusual eye contact	Acquisition of language/other skills
Integration of gaze [etc.] during social overtures	Qualitative abnormalities in reciprocal social interaction
Shared enjoyment in interaction	Restricted, repetitive, stereotyped patterns of behaviour
Spontaneous initiation of joint attention	Abnoramality in general behavior
Quality of social overtures	
Response to joint attention	
Stereotyped/idiosyncratic use of words or phrases	
Hand and finger and other complex mannerisms	
Unusual sensory interest in play material/person	
Intonation of vocalizations or verbalizations	
Unusually repetitive interests or stereotyped behaviors	

5.3.1. Overview

Abbas [123] et al. proposed a multi-modular AI-based system for diagnosing autism. It is composed of a parental questionnaire provided by the caregivers and a video analysis portion containing videos of children were uploaded by the parents, and a clinical module. Each of the modules recognized autism individually. The parental module and clinician module were trained using the ADI-R dataset, and the video module was trained using the ADOS score sheet. These modules could predict 3 classes that are positive, negative, and inconclusive. Gradient boosted DT was the selected ML model that was trained.

Data collected from databases were classified using a binary classifier, and only the correct predicted results were used to train the final runtime classifier. An intermediate classifier was imposed to filter the misclassified samples. For the parental modules feature selection, 18 out of 72 questions were considered for children aged less than 3 years, and 21 questions were considered in the case of the above 3 years aged children. From the videos, 3 minimally trained analysts answered questions from videos. The video model was trained with variance and bias to tackle skipped questions. Feature extraction from the clinicians module was from a questionnaire where the questions were prioritized over the parents questions. 13 questions were selected for the children aged below 47 months and 15 questions for children aged over 4 years. These modules were tested with data individually, and the outcome from them was considered a probability that was merged mathematically. The proposed architecture achieved 0.92 AUC where sensitivity was 90%, and specificity was 83%.

ADOS module is a time-consuming screening process of autism diagnosis and needs good supervision of an expert. Wall et al. [124] tried to reduce the features of ADOS module 1 so that this process can be completed with less amount of time. They have used WEKA to check 16 ML classifiers' performance based on accuracy, sensitivity, and specificity. They found that ADTree performed the best with almost 100% accuracy, 100% sensitivity, and 94% specificity by using 8 out of 29 features, which was 72.4% reduction of the features that reduced time requirement.

Wall et al. [125] proposed an ML model to diagnose children with autism in a concise and effective way. Autistic diagnostic interview-review (ASD-R) is the gold standard for the diagnosis of autism. However, it consists of 93 questions and needs 2.5 hours to complete. They proposed that 7 questions could be used to diagnose those patients that achieved 99.9% accuracy. They tested 15 ML algorithms and found that the alternating DT algorithm performed the best with an accuracy of 99.9% on the training data. They used 1962 cases diagnosed with autism for validation and observed that the model misclassified only one sample. They reduced 93% of the questions, which accelerated the diagnosis

Journal Pre-proof

process.

Abbas et al. [126] proposed a quick, low cost, and easy to use autism screening tool which used both video and questioner. The use of 2 sources of inputs gave them better confidence in the prediction. They performed feature selection, feature engineering, and feature encoding, which was a new addition in this research field. They used features from ADI-R for the questioner part and ADOS features for the video screener part. The data was collected using the Cogona application, that is popular for autism maintenance. They selected the most important features by bootstrap grid search, which helped them to achieve an AUC of 0.958 using the RF algorithm for the questioner data. Video features were predicted using the RF classifier. L2 regularized LR was used for combining these 2 models to classify autism.

Table 8: Overview of the reviewed research works related to autism Detection by ADOS and ADI-R screening tools and ML, AI and IoT

Cite	Age Group	Algorithms / Models Used	Results
[123]	Child	Gradient boosted DT	Sensitivity: 90% by Boosted DT
[124]		Alternating DT	Accuracy: 100% by Alternating DT
[125]			Accuracy: 99.9% by Alternating DT
[126]		RF	AUC: 0.958 by RF
[127]		LR, RF	Accuracy: 95% by LR
[128]		LR, SVM, Logistic model tree	Accuracy: 98.27% by LR
[129]		LR, SVM	AUC 0.96 by LR
[130]	All ages		Accuracy: 88.9% by LR
[131]	Child, Adult	SVM	UAR: 88.2% by SVM

Video-based autism diagnosis techniques are becoming popular as the parents of the patient find it troublesome to answer so many questions of different methods like ADOS or ADI-R. A short video of the patient can be used instead from which experts can find the right information. Abbas et al. [127] proposed a combination of questioner and video-based autism diagnosis system. They took data of 162 children to collect features of ADOS and ADI-R. Cognoa application was used for gathering the information. 2 RF algorithm-based models were used for 18 months to 3 years old children and 3 to 6 years old, which

Journal Pre-proof

Journal Pre-proof

used 17 and 21 questions. The video screener was used to answer 10 questions, which was also trained using RF. L2 regularized RF was used to combine these models, which diagnosed autism with a 95% confidence level. They also showed how home videos with some control information could speed up the diagnosis process of autism to a great extent.

Kosmicki et al. [128] used the ADOS module 2 and module 3 for finding the minimal feature set which could successfully predict autism. They used 8 ML algorithms for this purpose. The step-wise backward feature selection method was used for the reduction of features. 2 models were trained separately on the data of 4540 samples. For module 2, 98.76% accuracy was achieved by LR and logistic model tree. For module 3, SVM with RBF kernel achieved 99.83% accuracy. Module 2 used 9 out of 28 features, and module 3 used 12 out of the 28 features for achieving these results. This method reduced 55% features and helped in the early detection of autism.

Levy et al. [129] proposed a sparse ML technique to find the subset of the autism features. They tried to reduce the features of ADOS module 3 and module 2. They enforced sparsity by adding regularization techniques in 17 unique ML models. Augmented features with gender and age were used to achieve the reduced set. They used 10-fold cross-validation with a grid search to find the subset of the features. Penalization terms were added with the models to get the desired sparsity. LR with L2 regularization and linear SVM with L1 regularization achieved the best results with 10 and 5 features, respectively, providing an AUC score of 0.95 and 0.93.

Tariq et al. [130] used a video-based method for detection of autism. They used a web portal to remotely collect the videos. The video raters observed the uploaded videos and collected 30 features from these videos. This took each rater a median time of 4 minutes. They used 8 ML models for classification. They trained the model using ADOS and ADI-R. They found that a 5 feature LR classifier yielded the highest AUC of 92%. The accuracy of the LR-5 model was 88.9%. SVM also performed well with 85.4% accuracy, but the specificity was 54.9% only. The diagnosis of autism can be more accessible if a minimal

Journal Pre-proof

set of features was used for prediction.

SVM is a great ML tool for classification, and autism can be predicted using this. Hauck et al. [131] proposed an SVM based autism diagnosis method using the ADOS and ADI-R features. They trained the model with 2500 records and performed feature selection. They also used clustering, where 4 clusters were selected based on ADOS modules. They added demographic information and IQ level with the data. They achieved 85.6% to 94.3% sensitivity by taking 10 features. With Linear kernel, they achieved 88.2% UAR, and with the RBF kernel, the UAR was 87.2%. They showed that a better specificity and sensitivity could be achieved by using 7 to 10 features for the prediction of autism.

5.3.2. Performance Comparison

ADOS and ADI-R screening techniques need clinicians participation in autism detection. Here, researchers tried to use ML and Deep ML classifiers for detecting autism from ADOS and ADI-R screening data. Some of them achieved remarkable accuracy and sensitivity. Wall et al. [125] achieved 99% accuracy in autism detection using DT. They also adopted several ML classifiers later [124] and achieved 100% accuracy with 100% sensitivity using alternating DT. Kosmicki et al. [128] achieved 98.20% accuracy using LR. Abbas et al. [126] acquired 98.2% specificity in autism detection, where sensitivity was 62.4%. Abbas et al. [127] acquired 95% accuracy by adopting LR. Abbas et al. [123] acquired a UAR of 87% where sensitivity was 90%, and specificity was 83%. Figure 7 provides a comparison of the research works based on accuracy, sensitivity, and specificity.

5.4. Research Works on Autism Detection from Eye Movement, Kinematic Features and Different Screening Tools

Apart from the above mentioned screening tools, researchers have explored kinematic features, eye movement, electroencephalogram (EEG) data, cognitive response, and several behavioral data. These data were classified using several ML and AI classifiers to predict the class label. M-CHAAT-R [132], ISAA [133],

Journal Pre-proof

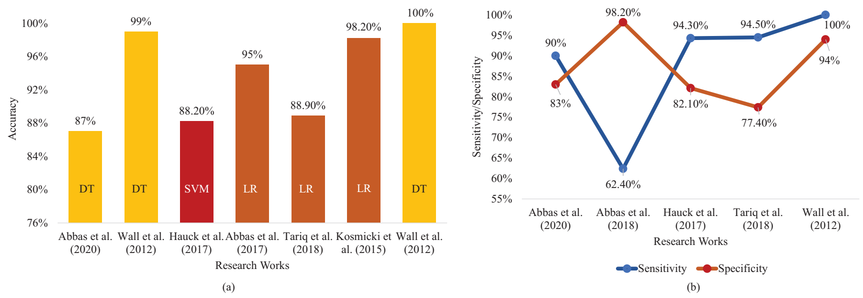


Figure 7: (a) Performance comparison of the selected research works that used ADOS and ADI-R screening tools based on accuracy. Highest accuracy achieved by the researchers was 100%; (b) Performance comparison of the selected research works that used ADOS and ADI-R screening tools based on sensitivity and specificity. Highest sensitivity achieved by the researchers was 100%.

and childhood autism rating scale (CARS) [134] are 3 more screening tools which are based on questionnaire. Table 9 describes the subject area of the questions of these 3 screening tools. Table 10 provides an overview of these kinds of research works.

5.4.1. Overview

Talebi et al. [135] proposed an ANN architecture to find causal relations between different zones of the human brain. They have used EEG data from 11 ASD patients and 19 typically developed human for this research. In the pre-processing stage, they removed noise and artifacts from the samples. They used the phase randomization function to produce 100 surrogate data for testing purposes. The ANN model was comprised of 15 hidden nodes. They utilized a gradient descent algorithm with momentum for dealing with the errors. They gave a lagged sample as input to the model to predict the subsequent sample. Based on the connections of the neurons in the ANN, the different brain regions' connectivity measures are determined. They have found that for the ASD patients, nonlinear information inflow was larger in the frontal, parietal, and left occipital regions, and for the typically developed people, the right occipital and right temporal portions showed higher non-linearity.

Journal Pre-proof

Table 9: Considered subject areas during creating questionnaires of M-CHAT-R [132], ISAA [133], and CARS [134] dataset

M-CHAAT-R	ISAA	CARS
Can follow direction or not	Social relationship and reciprocity	Relating to People
Deaf or not	Emotional responsiveness	Emotional Response
Playing pretend or make-believe	Speech-language and communication	Imitation
Like climbing on things or not	Behavior patterns	Body Use
Unusual finger movement	Sensory aspects	Object Use
Points finger to something or to get help	Cognitive component	Adaptation to Change
Points finger to show something interesting		Listening Response
Interest in other person		Taste, Smell, Touch
Show things to share with others		Visual Response
Responsiveness when calling by his/her name		Fear or Nervous
Understands smile and reply with a smile		Verbal Communication
Get upset by everyday noises		Activity Level
Walk or not		Nonverbal Communication
Eye contact		Intellectual Response
Tries to copy someone or not		General Impression
Follows someone's activity or not		
Tries to get attention		
Understands what someone says		
Look at someone's face to see how he feels about something unusual		
Like movement activities or not		

Journal Pre-proof

Journal Pre-proof

Table 10: Overview of the reviewed research articles related to autism detection using kinematic feature, eye movement, EEG data, screening tools and ML, AI and IoT

Cite	Data Source	Data Type	Algorithms	Results
[135]	30 subjects	EEG data	ANN	Difference in non-linearty pattern
[43]	ISAA	Questionnaire	NB, KNN, SVM, RF	Accuracy = 93.3% by RF
[80]	M-CHAT-R (Child)		ANN	Accuracy = 96.7% by ANN
[85]	CARS (Child)		Auto-encoder	Accuracy = 86.96% by Auto-encoder
[136]	NDAR dataset	Behavioral data	DT, RF, SVM, GNB, LR	Accuracy = 100% by DT
[137]	638 (Child)		ANN	Accuracy = 92% by ANN
[101]	10 (Child)	Heart rate	IoT-BRB	AUC of BRB > Fuzzy
[138]	500 (Child)	Cognitive response	CARMRMR	Similar accuracy as clinicians
[65]	43 (Child)	Kinematic movement	SVM, LDA, RF, KNN, DT	Accuracy = 88.37% by KNN
[139]	44 (Adult)		SVM	Accuracy = 78% by SVM
[110]	102 (Adolescent)	Responsiveness	Fisher's exact test, LR	Accuracy = 73% by LR
[140]	71 (Adult)	Eye movement	LR	Accuracy = 75% by LR
[141]	130 (Child, Adult)		SVM	Accuracy = 83.41% by SVM

Achenie et al. [80] proposed an ANN-based approach for detecting autism from a questionnaire. They collected data of 16168 toddlers whose ages were in the range of 16 and 30 months. They divided the dataset into different subgroups such as white, black, male, and female. There were 14995 total samples, and out of them, 4498 samples were selected for training. They used different feature selection techniques to select essential features from 20 features of M-CHAT-R. The entropy feature selection method selected 18 features, and it provided the best result. They showed the output of the individual subgroups by creating different ANN models. However, in the entire set, they achieved the highest accuracy of 96.7%, with 18 features selected by the entropy. This method achieved a sensitivity of 73.8% and specificity of 99.9%.

Florio et al. [137] used an ANN model to diagnose autism. They collected 638 cases and diagnosed them by professional clinicians, where 50% of them were of ASD patients, and 50% were of development disorder patients. Then they used these data to train an MLP network. They have used questionnaires of the developmental behavior checklist, along with the age, sex, and IQ level of the subject. They also collected data of 100 different cases for cross-validation.

Journal Pre-proof

For the training set, they have found 92% accuracy, which is better than that of LR (82%). For the cross-validation dataset, this model produced 80% accuracy.

Alam [101] et al. adopted an IoT-Belief Rule Based (BRB) system to collect data and classify autism. Data collection was done using an IoT-based architecture where a microphone was used for collecting behavioral data, EMG sensors were used for motor data collection, and heart rate sensors gave the heart rate of the children. A SD card was used for storing data in Arduino. After that, a database was collected from the SD card using the RF module and made available to the BRB system. BRB system was consist of 3 layers. Presentation layer was used for interacting with the user, application layer was utilized to prepare module by cooperating with deduction motor, data processing layer was created to store belief rules, and the data which were collected from the sensor. Belief Rule Based Expert System calculated the autism level from signs and sensor data, which were validated by the physician. They acquired sensor data from 10 persons, and then they were given input to the BRB system. The performance was analyzed using AUC, and BRB achieved better AUC and reliability than the Fuzzy system.

Che et al. [85] proposed an auto-encoder based approach to detect the severity of autism. The auto-encoder is a NN which consists of 2 networks that are encoder and decoder. It tries to find out the optimal feature set by reducing errors through encoding and decoding. In this work, they collected data according to CARS. A total of 122 samples were collected. Each sample was assigned to one of the 3 target classes that were no autism, mild autism, and severe autism. Each sample had 27 attributes and the dataset was divided into train (99 samples) and test set (23 samples). Data was passed through several pre-processing steps such as one-hot encoding. Then a set of sparse auto-encoder was set up sequentially where the output of one encoder was the input of another. The sparsity parameter and the hidden neuron number was set through grid searching. 5-fold cross-validation was performed to find out the effectiveness of the model. The proposed architecture achieved 86.96% accuracy in classifying samples into no autism, mild autism, or severe autism.

Journal Pre-proof

Journal Pre-proof

Pavitra et al. [43] analyzed the performance of ML architectures in ASD detection. They used the ISAA dataset that contained 40 features under 6 domains, and the total number of instances was 100. Each domain consisted of 4 to 9 questions, and a score between 1 and 5 was given for each question. They classified each instance into 4 classes: no autism, mild, moderate, and severe autism. They evaluated the performance of NB, KNN, RF, and SVM classifiers in this work. RF achieved the highest accuracy of 93.3% and the lowest error rate of 6.7 in classifying ASD.

Xhao et al. [65] adopted an autism detection method where they used ML algorithms to classify autism from Restricted Kinematic Features (RKF). They created a dataset where 43 children (20 ASD, 23 No ASD) participated in performing a particular motor task. They calculated a total of 18 features for each of the children. SVM, KNN, LDA, DT, and RF were used for classification purpose. At first, the feature set was reduced. Only discriminating features were given input to the model, and the feature with p-value < 0.1 was selected for the next process. Then forward feature selection method with all the ML algorithms was trained and tested. It was found that KNN achieved the highest accuracy of 88.37% using 4 features. KNN acquired 85% sensitivity, where the specificity was 91.30% while classifying ASD.

Yerramreddy et al. [136] proposed an ML model for the prediction of autism and types of ASD. It is a two-phase model which at first checked for whether the subject had autism or not and then checked the ASD type. They used 7 ML algorithms on the National Dataset for Autism Research (NDAR). The dataset had 63% data of autism patients with 20 behavioral and person-specific features. For checking ASD types, they used the UCI dataset. If the model predicted the subject as no autism, then the second phase was used to find out if the subject had ASD or not where 18 questions were asked to the subject. For the first phase, RF performed very well with 90% accuracy and 90.16% sensitivity. For the second phase, extra tree classifier, RF, DT provided 100% accuracy and sensitivity. They built an android app for collecting information about the subject.

Journal Pre-proof

Vabalas et al. [139] proposed an approach for autism detection using SVM classifiers with RBF kernel from eye movement and kinematic features. They collected kinematic and eye movement features from 44 adults (22 autistic, 22 non-autistic) using a motion tracker and eye tracker while watching videos. They wanted to detect autism based on the response rate of autistic individuals while watching movements and following it. After collecting data, they handled the missing values and performed z-score normalization. They used different feature selection algorithms such as t-test, ensemble feature selection, and so on to reduce features for making a robust model. They performed k-fold cross-validation and tuned the SVM classifier. They tested the model by using 3 set of features, that are only kinematic features, only eye movement features, and both kinematic and eye movement features. After several trials, they found out that SVM with the wrapped t-test feature selection method achieved the highest accuracy (78%) using a combined feature set.

Liu et al. [141] used SVM to detect autism from eye gaze coordinates and motion. They used an eye tracker to collect eye motion images. They collected data from 61 children (20 ASD, 21 typically developing, 21 IQ matched typically developing) and 69 adults (19 ASD, 22 intellectually disabled, 28 typically developed). They extracted a bag of words histogram representation of gaze coordinates where they extracted one histogram per image per subject. They also extracted a bag of words representation on gaze motion. They labeled all the images and then performed the subject level prediction, where they used SVM with RBF kernel. They tried several prediction procedures such as soft prediction where a value between 0 and 1 was predicted, and a hard prediction where only 0 or 1 was predicted. They tried several feature sets but found out the best result in trying the combination of eye gaze motion and coordinates features. In the child set, they achieved 86.89% accuracy and 0.9207 AUC using SVM. They achieved around 80.33% accuracy in the adult set using the same classifier.

Bertoncelli et al. [110] proposed an AI-based model for identifying the factors associated with ASD among adolescents with cerebral palsy. They used data

Journal Pre-proof

Journal Pre-proof

of 102 people (61: male, 41: female) as the subjects to discover the factors of ASD. They used Fisher's exact test to find out the factors of ASD. They found that rational decision making, feeding abilities, motor functioning, and communication functionality were the key factors that were working behind ASD. Then they used an LR algorithm to use these sets of parameters to assess an ASD patient. This model obtained 73% accuracy.

Yaneva et al. [140] used LR to detect autism from eye movement. They used different web pages and set up several tasks to find out features from it. They included data from 68 participants, where the first group had 30 participants (15 ASD, 15 No ASD), and the second group had 38 participants (19 ASD, 19 No ASD). The first group had to perform 2 tasks that were a browsing task where they explored a web page for 120 seconds and a searching task where they had to find an answer to a specific question within 30 seconds. For the second group, the tasks were a browsing task where they could explore a web page for only 30 seconds, a synthesis task where they needed to find answers to 2 questions, and found the answer to the third question by assessing the previous 2 questions within 120 seconds. They used 6 different web pages for browsing and answering questions, which could be divided into 3 difficulty levels. They also defined several areas of interest on the screen. From the recording, they extracted several gaze-based and non-gaze features. They found the best accuracy (75%) in the case of search tasks. They also found good accuracy in classifying ASD from browse task 1 (74%), synthesis task (73%), the second browse task (64%).

The type of autism is needed to identify in order to provide proper treatment to the patient. But without watching the cognitive response of the patient, it is difficult. Moreover, if the treatment is not started between 10 and 60 months of the birth of the child, the treatment procedure becomes problematic. Dutta et al. [138] proposed a model that could predict possible symptoms from the basic symptoms of the patient. This was done by using the history of previous patients. They craeted a model using ML and confabulation theory, which used cogency. Cogency is to compute the frequency of 2 events occurring based on

Journal Pre-proof

Journal Pre-proof

some condition. When a patient showed some symptoms, based on the minimum Redundancy and Maximum Relevance (mRMR) algorithm, other symptoms were predicted. They proposed an algorithm that was based on the mRMR algorithm and it was tested on 500 samples of autism cases with 35 symptoms and 10 autism types. These symptoms were validated by the experts, and their model achieved almost same accuracy to the experts.

5.4.2. Performance Comparison

Researchers have used EEG data, kinematic features, eye movement for autism detection. Yerramreddy et al. [136] achieved 100% accuracy from behavioral data for autism detection by using DT. Florio et al. [137] and Pavitra et al. [43] acquired 92.2% and 93% accuracy from questionnaire. Achenie et al. [80] used an ANN classifier and found 96.7% accuracy in autism detection from behavioral data. Xhao et al. [65], Vabalas et al. [139], Yaneva et al. [140] and Liu et al. [141] detected autism from eye and kinematic movement using ML approach and achieved more than 75% accuracy. A brief comparison of these kind of research works is illustrated in Figure 8.

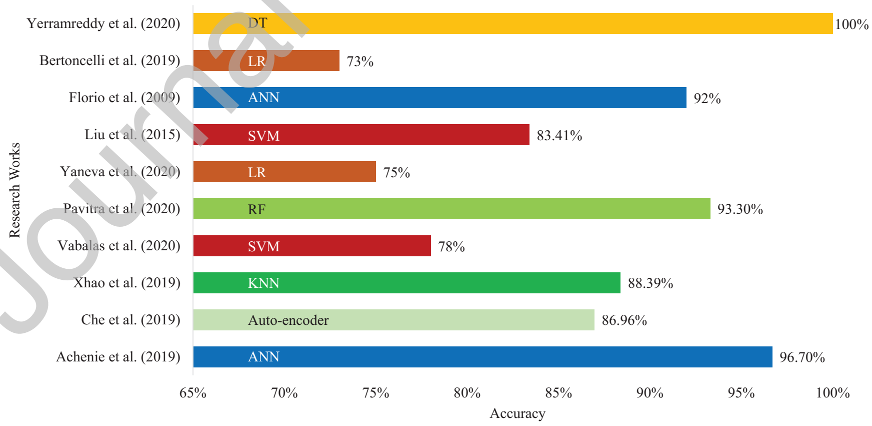


Figure 8: Performance comparison of some research works for autism detection based on accuracy. Different features such as. eye movement, kinematic feature, and so on have been used in these research works. Highest achieved accuracy among these works is 100% by Yerramreddy et al. (2020) [136].

Journal Pre-proof

6. AI, ML and IoT for Autism Management

Signs of autism can be shown within 3 years of age [142], and significant improvement in these children's skills can be assured by therapy and learning. Autistic individuals are very much attracted to visual graphics and digital devices, which help them to learn a lot faster. Hence, many researchers proposed AI-based gaming [143, 144], and object sensing-based visual graphics [104] for training autistic person. They also need constant monitoring and help. Emotion recognition, activity recognition, response monitoring, and so on are very much needed for all of them throughout their entire life. Monitoring the health condition of autistic individuals is also required as they become physically weak. Different smart devices are proposed by researchers to ensure proper health monitoring. In this section, the research works related to autism monitoring, intervention, therapy and assistance using AI, ML, and IoT are described. Figure 9(a) illustrates the usage of some of the most used sensors for autism management, Figure 9(b) provides a distribution of the selected research works related to monitoring, intervention, and assistance, and Figure 9(c) shows a basic environment for ensuring monitoring and assistance through AI, ML, and IoT for autistic person. This environement should have sensors that would collect environment data and also will find out the current state of the subject. A data storage should be incorporated to store previous records. An AI-enabled decision making system will help in taking decision based on current sensor data and the previous data. Actuators will act according to the decisions taken by the intelligent system to ensure proper management of the subject. Table 11 provides an overview of the selected articles, and Table 12 shows the outcome of these research works.

Sula et al. [104, 145] proposed a system to teach vocabulary and mathematical skills using the JXTA-Overlay platform and SmartBox device. They used a JXTA-Overlay platform to establish communication between children, caregivers, and therapists. They used the RS232C port to control the peers, motors, LEDs, and UUID in order to uniquely identify a peer. SmartBox was used to

Journal Pre-proof

Journal Pre-proof

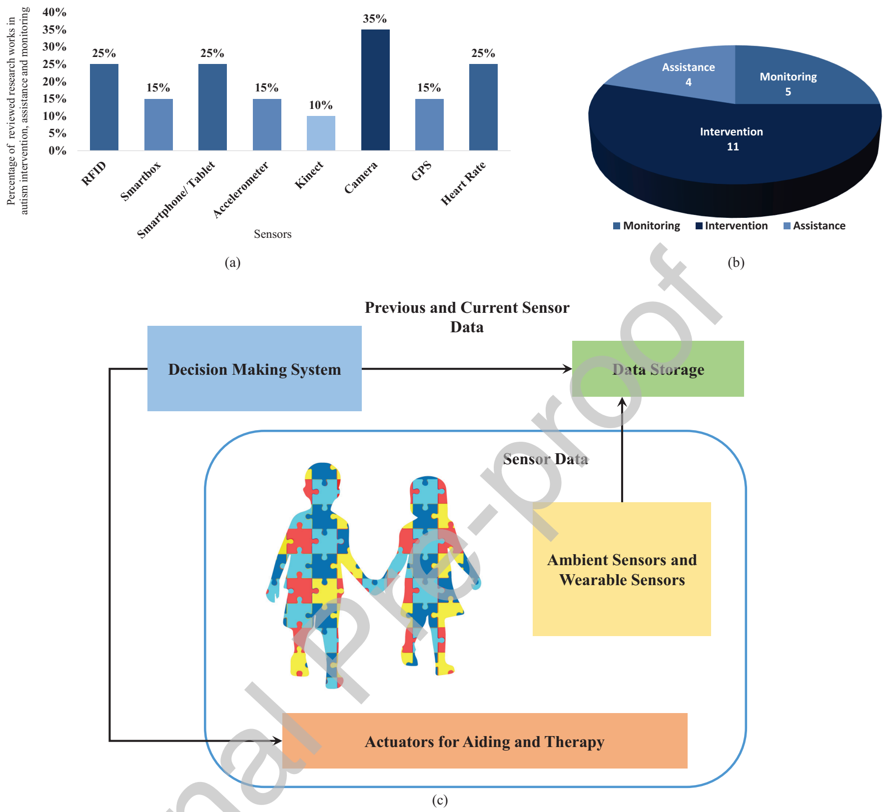


Figure 9: (a) Most used sensors in reviewed works related to autism intervention, monitoring and assistance. Camera has been used in the highest 35% of research works as images and videos are one of the most effective way of monitoring. RFID, smartphones, heart rate sensors are also used in signification amount of research works; (b) Distribution of the reviewed research works. Most of the reviewed articles in autism intervention, assistance and monitoring porting is related to autism therapy and learning; (c) A basic architecture for ensuring monitoring, intervention and assistance of autistic individuals through IoT, ML and AI. Sensors should inform the intelligent system about the state of the subject and also about the environment. The AI and ML enabled decision making system should asses current and previous data, detect the present situation and provide necessary assistance or take measures using actuators.

Journal Pre-proof

provide several functionalities and sense different activities such as sensing hand movement, sensing body movement, vibrating chair or bed, light control, smell control, and so on. They used chair or bed vibration to make the child relax, light, and smell control to get attention and sound control to make child-focused. They embedded RFID tags on the top of the objects. When children touched it, it opened a relevant PowerPoint slide and would pronounce words. They experimented with the proposed system where hand movement was recorded and found that the inclusion of SmartBox significantly improved the response time and total study time.

Amante et al. [146] proposed a mobile application that could be used to acquaint autistic individuals with first-aid. There were 6 stages in the game, and every stage contained more sublevels. The characters in this game were intimated using AI. The user had to pass each sublevel to level up in the game, and knowledge would be piled up as the game progressed. The score was calculated according to their knowledge, and a scorecard was showed in every sublevel.

Whalen et al. [152] proposed a technology-aided intervention for training children affected with ASD. They used google glass and mobile applications to train social skills. The proposed method was a low cost, versatile system for treating ASD. A google glass-based mobile application was developed so that it could guide children during social interaction. The system was tested in 10 children suffering from ASD, whose mean age was 13.2 years. The children were engaged in a restaurant themed interaction where they used this app and google glass. The detection accuracy of this app was 97%, where recognition accuracy was around 89%. Children's average response time was 2.5 seconds during this experiment.

Selkowitz et al. [99] proposed an AI-powered Emotion Demonstration, Decoding, Interpretation, and Encoding (EDDIE) system for children with ASD. It was proposed for therapeutic purpose for children who have difficulty in expressing emotion. The proposed system contained servo motors, a MIDI interface, and 3D facial components. The system's vision was achieved using Kinect, which was operating from behind the EDDIE and 1 meter from the subject. It

Journal Pre-proof

Table 11: Overview of the selected articles related to therapy and monitoring of autistic individuals

Cite	Age Group	Application	Sensors / Devices Used
[92]	Not Specified	Assistance	Gas sensor, camera, accelerometer, microphone
[77]		Monitoring	Facial expression recognition from image
[146]		Training	Smartphone
[99]		Therapy	Kinect
[147]			No sensors, facial data was used
[148]	Children		SmartBox,RS232C, RFID
[67]			No sensors
[149]			Tablet, camera
[150]			Video, audio, physiological
[104, 145]		Training	SmartBox, RS232C, RFID
[151]			RGB Camera
[152]			Google Glass, Smartphone
[153]		Monitoring	Badge sized ultrasound sensor
[100]			Temperature, humidity, Kinect V2, pressure, camera
[154]			Blood pressure, body temperature, heart rate, speech signal
[155]			Heart rate
[91]		Assistance	GPS, Heart beat, sound, accelerometer
[105]	Adult		Smartwatch, smartphone, RFID
[156]	Children, Adult		GPS, smartphone

could identify the subject's facial recognition from muscle movement and Facial Action Unit (FAU), where each FAU identified unique expression. EDDIE was able to operate in 4 modes that were decoding mode where EDDIE showed the subject an emotion and instructed to express it verbally, encoding mode where EDDIE instructed the subject to do emotion, and it checked whether the subject could do it or not to provide appropriate feedback, encoding, and decoding mode where both were done continuously, free from a mode where the subject could perform any emotions and EDDIE would mimic it. The proposed system was reliable, low cost and increased the knowledge of the subject in the form of a game that maximized its impact.

Veeraraghavan et al. [147] adopted a knowledge-based system to detect development disorder and to improve social skills. They proposed a knowledge-

Journal Pre-proof

Journal Pre-proof

based screener to analyze a child's weakness and progress. This was composed of 2 screeners: a delay screener for screening development delays in motor and a social delay screener for screening in language, social and cognitive function. This screener had a knowledge base containing factual data and heuristics and an inference reasoning engine to form a line of reasoning to find out ways in order to solve the problem. The gaming system used AI concept, NN, backpropagation, Reinforcement Learning (RL) that was available in different local languages, and adaptive to different scenarios to teach vocabulary, social skills, mathematical skill, and so on. The model was built using 3 tiers where client tier was used to communicate from the browser side, a middle tier for executing dynamic web pages and retrieving and sending data, and a server tier that contained data. This training process should be done in 2 cycles within 6 months, depending on the child's progress.

Sula et al. [148] suggested using smart devices to teach autistic children and monitoring them through sensors. They implemented a JXTA-Overlay platform to establish communication between children, therapists, and caregivers, where they used an RS232C port, USB port, to control peers attached to the system. They also used SmartBox, which comprised several sensors to create a relaxed environment and monitor the children. They used RFID tags on the objects, and when children touched those objects, a page with the information of that objects was popped up on the screen. It also generated a voice in their native language, which eventually taught the children about their objects. This learning environment could help the autistic individual in earning mathematical and social skills.

Palestra et al. [151] created an AI-based social robot for ASD affected children. At first, they found that the robot should have capabilities like emotion recognition, eye contact detection, language understandability, and so on. Afterwards, they presented a detailed workflow of this robot which described the training procedure of an ASD patient to do eye contact with others using the proposed system. They proposed a 3-level (easy, medium, and hard) training scheme. Their model used the Viola-Jones detector to detect the eye. Then they

Journal Pre-proof

Journal Pre-proof

subtracted white portion from the eye to find the iris, which was divided into 8×8 sub-portions. The center was the pupil, and if it was aligned, they called it a contact. They tested this method on 3 children and saw 73.3% of children could pass the easy level, but only 28.89% of children could pass the hard level. Finally, they suggested that the other features should be incorporated to make a complete system in the future.

Afrin et al. [77] proposed an AI-based approach to recognize facial expression recognition of autism individuals. At first, they took the image as an input and removed noise from the noise using a median filter. They segmented the filtered image. GLCM was used to extract features from the image, and a rank component strategy was taken to select important features. Then a simple CNN was introduced to classify the image. They simulated the whole architecture and found that the architecture was successful in classifying facial expression.

Tang et al. [100] suggested a prototype where different sensors were attached with toys for sensing emotion and monitoring behavior. They discouraged to use the wearable sensors as autistic children could feel uncomfortable. They took physiological data from Microsoft band 2 for collecting heart rate and perspiration. They obtained movements using Kinect, and these movements were tracked using a pressure sensor. They also collected the environmental data of the room using temperature and humidity sensors. The sensors were connected to Arduino Uno, base shield, and Yun shield that could send real-time data to servers through Wi-Fi. Local computers could collect data and analyzed them. They also set up a table that could show different colors according to the emotion of the child. They tested the environment in both the subject's sitting and standing condition, where they could detect the sad and happy state only.

Sumi et al. [91] proposed an assistance system for caregivers of ASD patients. They proposed a smart wearable device that could detect the patient's position, heartbeat, sound, and movement. These sensors used a wireless interface to transmit data to the parents, caregivers, and external repository. GPS sensor was used for location tracking, and an accelerometer sensor was incorporated for finding repetitive patterns in the patients. They took 12 subjects from a school

Journal Pre-proof

dedicated to children with autism. The children kept the device with them for 15.96 minutes on average for an experimental time of 30 minutes. They used a Fuzzy Expert System (FES) for this model and achieved 89% accuracy.

Table 12: Outcome of the selected articles related to therapy and monitoring of autistic individuals

Cite	Methods and Protocols	Results
[153]	IoT Device, Sensor based	Matched 80% to 86% time with camera data
[104, 145]	Sensor based, P2P Communication	Study Time reduced to 305s
[77]	CNN, GLCM	Identified simulated facial expression
[151]	Robot based, Viola-Jones detector	Highest percentage of eye contact = 77.3%
[152]	Mobile Application, Sensor based	Interaction detection accuracy = 97%, 2.5s response time
[91]	Wearable device, FES	Accuracy = 93%
[92]	Sensor based, FES	93% care givers satisfaction
[149]	Web Application, Active ML	Highest mean object recognition accuracy = 96.7%
[154]	Wearable device, SVM	Health condition prediction Accuracy: 86.67%
[67]	Web based game, RF	Accuracy of Emotion detection from speech = 72%
[155]	Sensor based, LR, SVM	Stress Detection Accuracy = 93% by SVM
[150]	Robot based, Feed forward NN	60% similar affect of therapy as human expert
[105]	Sensor based	Only method proposed
[156]	Event sensing, location sensing	
[100]	Sensor based, WiFi	
[148]	Sensor based, P2P Communication	
[146]	Virtual Reality, AI gaming	
[99]	Robotic based	
[147]	Knowledge based , AI gaming	

Khullar et al. [92] suggested a system for assisting caregivers dealing with ASD patients in the form of a playing element. They collected data of 10 ASD patients and 5 healthy people. The system comprised of a gas sensor, camera, sound sensor, and accelerometer which were used to collect data from the environment. A FES was used for the evaluation of the data. The FES's output was sent to an external server, which determined whether to transmit an alert to the parents and caregivers of the ASD patient or not. An email-based system was proposed for the alert system. They also implemented a response system that would help the patient to be calm until external help was available

Journal Pre-proof

for them. The caregivers provided a rating of over 5 in 93% of cases for this system, and the average score for the alert system was 7.3. The average rating was 7.1 in the case of feedback system.

Shi et al. [153] proposed a small badge size wearable ultrasound sensor-based system to analyze the social interaction of children. The badge-sized sensor was operated using 40 kHz ultrasound signals which could detect the other badges within a 220-degree cone and calculated the distance between them. These badges were attached with t-shirts of autistic students, a base station collected the sensing data, and a software provided real-time visualization of data. These badges could detect face to face time, distance, and activity levels, which are essential for analyzing social interaction levels. They experimented the proposed badge in a preschool with 3 children aged 3 years. A camera was also attached, which could also detect interaction through software. However, the badge and camera both captured interaction, and their interaction recognition was matched in 80% to 86% of events, which ensured the wearable sensor's capability.

Einarson et al. [105] proposed an IoT based prototype for helping parents with ADHD in their daily life. In their system, the smartwatch was used to monitor pulse, which could indicate stress. Data obtained by the smartwatch was sent to the smartphone through Bluetooth, where the smartphone stored data in the cloud. The user could also provide the current status of the patients through an app. Patients with ADHD often forget to take necessary things with them when they go outside. To solve this, they proposed using a calendar which could give reminder and RFID was attached with the things they needed every time. Whenever, the subject went out, the RFID was scanned and alarmed him through smartphone notification in case of not carrying an important object. The problem of these prototypes is the dependency on smartphones and wrong heart rate alarm, which may cause due to exercise.

Tang et al. [156] proposed an interactive communication system for autistic individuals to communicate through exchanging pictures. This system could sense locations such as schools, coffee shops, and so on. It was able to do behavioral modeling and computation sensing. It could generate picture cards

Journal Pre-proof

through location sensing, and by selecting pictures, autistic individuals could request items. The communication could be done through a WeChat message or vibration signal in case of wearing a bracelet that was developed by the researchers.

Radwan et al. [149] proposed an active ML framework for teaching object recognition to autistic children through a web application. In active ML, the classifier is trained with a small subset of information, and it takes more informative instances from unlabeled data pool and requests for labels from experts. In this work, they measured the uncertainty of an object through 3 parameters that were response correct (correctly classified by the children or not), response latency (time needed to classify it), and required number of auditory stimulus repeat. Uncertainty was measured by combining them using a weighted approach. Based on this value, a set of n objects was created with the highest uncertainty value to teach the children in the next iteration. They chose 5 autistic children for trial and performed sessions in the school of the participants. They selected 30 objects from 5 categories, and the objects were familiar with the children. There were 31 images of each object, and an auditory stimulus was recorded for them too. These images were assigned to different difficulty levels. Different subsets of images were created to assess and train the child with different images. 4 images with audio were given for the child in the learning process, where they were told to respond to it. A positive or negative response was given to the child in the form of RL to teach them the object. In the full treatment process, Active ML used 4 blocks. In each block, 2-4 teaching trials were done before 10 assessment trials. The best treatment trial was performed at the final stage for 2-3 sessions. AML was proved very useful in 4 out of 5 children in the case of learning objects.

Mamun et al. [154] proposed an ML and 5G network-based system for monitoring the health condition of autistic individuals in autism centers. They used different wearable devices and collected blood pressure, body temperature, heart rate, speech signal, and body motion. An ID was assigned for each person in the autistic center, and previous history and details were embedded in the

Journal Pre-proof

Journal Pre-proof

system. These data were collected at a regular time interval and send to the database through a 5G network. SVM was used to analyze data and found out abnormality from it. The system notified the center, activated the alarm system, notified the nearby ambulance and hospitals in case of any abnormality. It handled the false alarm by collaborating with 2/3 sensor values. They experimented the system with 15 autistic people. It showed 5 children in bad health conditions, where only 3 children were actually in bad condition. Hence, it correctly predicted the health condition with 86.67% accuracy.

Rouhi et al. [67] proposed a web-based game for teaching emotional behavior to autistic children. This game covered 4 emotional states (sadness, happiness, neutrality and anger). This game had 2 stages: training and evaluation. In the training section, it introduced the children to different emotions through animations. Then it tried to teach them the voice tone associated with different emotions. In the testing part, the children are prompted to detect emotions from played videos and audios. In the latter part of this section, this game asked children to perform some emotional activity. It could detect these activities through speech recognition. They used an RF-based classifier that could detect emotions from speech with 72% accuracy. In this way, the proposed game could help autistic children in learning emotional expressions.

Anxiety and stress are the biggest issues that an ASD patient faces, which can lead to a degradation of their health condition. Masino et al. [155] proposed an ML-based method to detect stress in children diagnosed with ASD. They used heart rate and beat to beat intervals of rested and active cases. Data of 38 patients were collected, and 20 statistical features were calculated from them. Firstly, the subjects were relaxed with 7 minutes of relaxing video to get the resting state physiology followed by a 4-minute transparent box challenge, where an incorrect key was provided to open the box. Then tangrams puzzle was provided to them for 5 minutes with an extra piece to make the puzzle unsolvable. Through this time, physiological data were collected. They used leave-one-out cross-validation to test the model and found that LR produced 87% accuracy, and SVM achieved 93% accuracy to recognize stress.

Journal Pre-proof

Patients with ASD show various patterns, and that's why it is very difficult to provide a generalized model for interacting with them. Rudovic et al. [150] suggested a personalized model for each child with ASD using their characteristics data and context. This can be used in robot-assisted therapy of the patient. They used a dataset of 35 children from Japan and Serbia. The data included video, audio, and physiological data of the patient. They used the proposed Personalized Perception of Affect Network (PPA-net), which was actually a feed-forward multi-layer NN. The data was split into 40%, 20%, and 40% for training, validation, and testing. The main goal of this model was to find the best performance of the robot's perception. This model achieved 60% of the human experts' effect and engagement that outperformed other ML-based models.

7. Smart City and Autism

As people are turning towards smart technology based automated cities, availability of these technologies to all classes of people should be the main consideration. ML and AI have been already introduced in the newest concept of smart city [157, 158]. A large number of the population is suffering from autism. Therefore, designing technologies and embedding them in the concept of smart cities is inevitable. There should be several technologies in roads, restaurants, transportation, offices, houses and even in educational institutions by which, an autistic person can get all the facilities that a normal human being gets. They should be able to roam freely, should be able to do everything as others do and enjoy the blessing of smart cities like others. In the smart technology enriched cities, autistic people should get the assistance through automated devices in restaurants and hospitals. Robots should be able to replace human to assist them in several procedures such as ticketing, doctor's appointment, order placement, and so on. Menu, counters, and services should be specially designed for them in a way such that, autistic individuals can easily understand those and perform all the things by themselves. They all should be tracked through

Journal Pre-proof

Journal Pre-proof

all the smart devices and cameras and monitored in a regular manner to assist them in any kind of problem. Traffic lights and control should be synced with GPS of the wearable devices that are worn by the autistic people, so that they can walk freely. Specific lanes and intelligent systems may be developed, which can easily guide them towards their destination. Self-driving cars can be a great help for them to reach their destination. Criminals often try to attack them as they are physically weak. They should be able to interact with police or helping hand by just a click of a button. Their data should be kept in confidential manner and should be available to appropriate authority whenever they are needed. Robots and sensors can effectively help them in schools and training. A special robot may be developed, which may have the ability to understand the needs, problems, and can read the expression of them to assist in gradual training, medical care, schooling and also during walking in the streets. These technological advancements can largely make them independent and make their hope of living individually in a smart environment. Figure 10 illustrates the basic elements of smart city that should be ensured for autistic people.

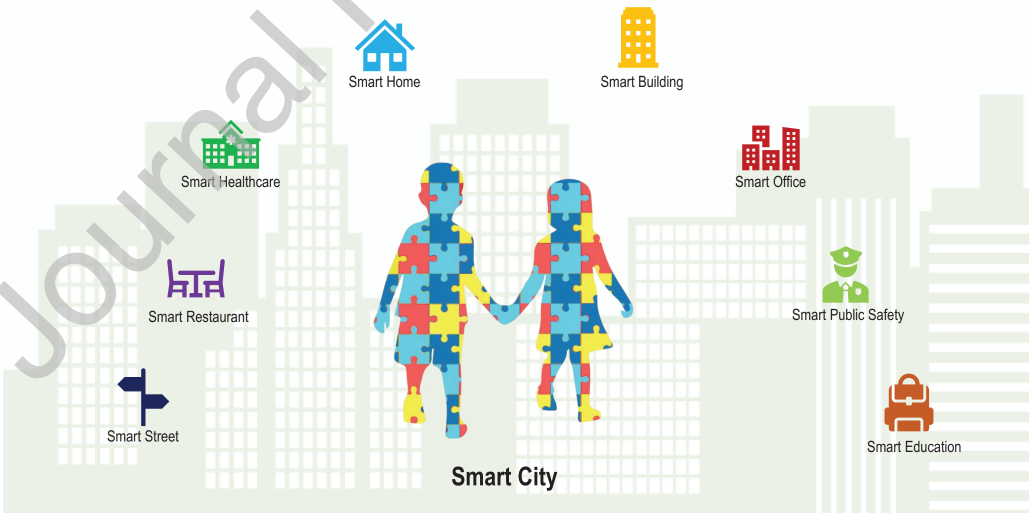


Figure 10: Autism in smart city. All the technologies used in healthcare, restaurant, street, education, public safety, office, home, building, and so on should be designed considering the autistic people to make their life easier.

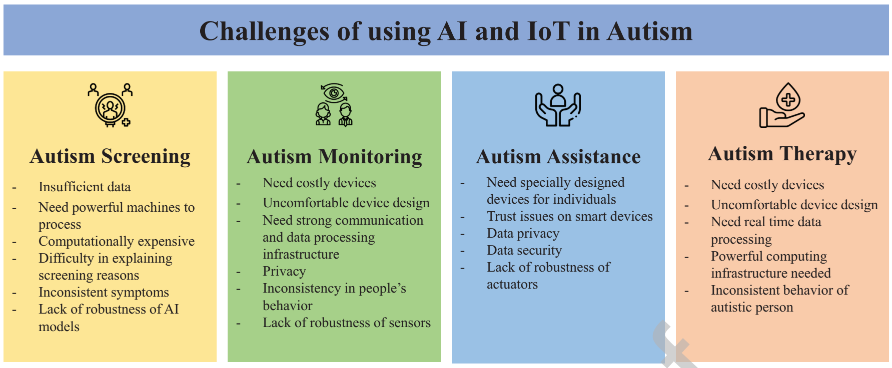


Figure 11: Challenges in using AI and IoT in autism screening and management.

8. Challenges and Recommendations

Inclusion of AI and IoT in autism management and screening has several challenges and requires more research attention. In this section, some challenges in this field and several research scopes have been described.

8.1. Challenges in Screening Autism

There are several challenges in the usage of AI and IoT in autism screening. Efficacy of AI-based approaches in screening autism largely depend on the available datasets. Though there are quite a few datasets, these data are not large enough to prove the performance. Collecting new data is challenging as they are considered as confidential and healthcare professionals can not share these data without proper permission. Data are also stored in unsuitable format. AI algorithms also need a very large computational power which is really hard to ensure everywhere. NN shows very promising result in autism screening but it is actually a black box and hard to describe. Therefore, there is always a difficulty in explaining scenarios in NN which may be a reason for not considering the NN methods in healthcare. Autism symptoms may vary person to person and it changes due to age. It is really costly to collect medical data constantly to get the pattern of the autistic people as they grow up. Robustness is another

Journal Pre-proof

Journal Pre-proof

question of AI approaches in autism screening because a false result may prove very costly in this field. Figure 11 illustrates some of the challenges in this field.

8.2. Challenges in Autism Management

Monitoring of an autistic patient is dependent on the reading of sensor data. Continuously collecting data using several sensors and devices is costly and requires large power. Sensor devices do not always provide correct reading and it might be the reason of wrong alarm provided by the AI-powered devices. Collecting real time data, storing them and taking decision by the virtue of AI need very strong communication infrastructure and very powerful computing devices which is difficult to avail. It is also uncomfortable for a challenged person to wear sensors all the time. There is always a question of privacy and data security in this sector. For providing assistance, IoT and AI are now being used widely. But, as these people are challenged, it is really hard to design a common device for all so that every autistic person will be benefited. Everyone needs a specially designed device for himself which is not a feasible solution. There is a question of data security which is also a common research area as these data are confidential, and should not be hacked or transferred to unauthorized person. Therefore, there is still some trust issues in using smart devices in autism management.

8.3. Recommendations

Detection, monitoring, therapy, and assisting autistic individuals using AI, ML, and IoT is a growing field of research. DL and ML have proved its efficacy in biomedical applications [159, 160, 161]. Most of the articles reviewed in this paper used ML, DL, or rule-based approaches for autism detection from MRI images or behavioral patterns. A combination of different input parameters such as clinical data, behavioral patterns, MRI images, attitude, and so on can be used together for finding patterns. It will provide a very good feature set and would be enough to distinguish between autistic and normal children. DL and ML can be used further for pattern and image recognition. State-of-the-art CNN

Journal Pre-proof

Journal Pre-proof

architectures such as ResNet [162], InceptionNet [163], MobileNets [164, 165], VGGs [166] can be introduced to increase precision in MRI image recognition to detect autism. As these datasets are large enough, systems should ensure parallel processing [167] and should be capable of handling big data [168, 169] and data uncertainty [170]. Blockchain has been used with AI and ML for data security purposes [171, 172] and it can be embedded for autism related applications as well. There is a research scope in this kind of works. Early detection of autism is also a research gap that should be considered.

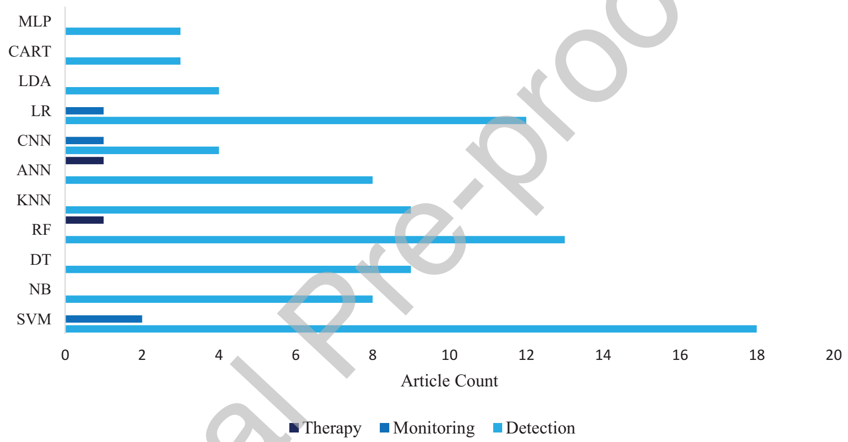


Figure 12: Usage of AI algorithms in autism. These algorithms are mostly used for screening purpose.

IoT has already proven its excellence in sensing environment and automation. It has also proved its usefulness in autism. Autistic children are very sensitive, and they can not wear or maintain devices properly. Therefore, researchers need to concentrate on a non-wearable sensor-based monitoring systems. Attention should be given to low-cost device design as families with autistic individuals go through many financial hardships. More robots and mobile applications need to be developed for assisting autistic people in learning. Most of the devices that were proposed in the reviewed research works have some limitations. These devices are not sufficient for learning. Hence, devices should be designed

Journal Pre-proof

in a way that they can be upgradable and proved as complete for helping autistic people. A possible system should have integrated non-wearable sensors such as camera, RFID, and so on, where RFID can be used for monitoring activities, the camera can be used to evaluate emotion, behavior, response rate, and so on. Video can be processed using Long Short-Term Memory [173], RNN, Gated Recurrent Unit [174] for monitoring their activity. Sound and visuals can be used for controlling them. Some mobile applications should be aligned with it, which will be operated using AI. Most of the existing research articles on management did not use AI algorithms for decision making, which is illustrated in Figure 12. AI is capable of recognizing the emotion, behavior, need, and mental state of the person, and robots, mobile apps, and other devices can be operated according to AI's decision. This will reduce the dependency on caregivers and clinicians as the person will be monitored all the time. These devices would help him to acquire necessary skills such as social skills, norms, expression, words, numbers, and so on. They will also be in a controlled and continuous learning environment, which will be very useful in increasing the brain development rate.

9. Conclusion

Autistic individuals are part of our society, but sometimes they are considered differently and also neglected. They go through a lot of hardship in their life and find it difficult to cope with the normal environment. They always remain dependent on others. IoT, ML, and AI can help them a lot to overcome this situation. IoT and AI-enabled devices can assist them to be self-sufficient. Autistic individuals are major concern in smart city concept too. Smart cities should have all the facilities for autistic people so that they can live a normal life without the assistance of others and enjoy all the modern amenities of the newest technology which will eventually make their life easier. Designing technologies and devices that have AI, can lead towards the goal of smart city. The ML and AI-enabled devices can help them in learning by evaluating their condition and can keep them within a controlled environment without the need

Journal Pre-proof

Journal Pre-proof

for any caregiver. They can also take the assistance of different applications to overcome their difficulty in understanding, ordering, and expressing. Early detection of autism can save a life from the extreme effect of autism. In this paper, 58 research articles related to the use of ML, AI, and IoT in autism detection, intervention, monitoring, and assistance were described. They were acquired from different repositories. A short overview of their works was provided and the articles were compared based on their performances. Some research scopes and challenges in this field were mentioned and provided some recommendations for further research works.

Journal Pre-proof

Journal Pre-proof

References

[1] M. L. Pennington, D. Cullinan, L. B. Southern, Defining autism: variability in state education agency definitions of and evaluations for autism spectrum disorders, Autism research and treatment 2014.

[2] E. S. Kim, L. D. Berkovits, E. P. Bernier, D. Leyzberg, F. Shic, R. Paul, B. Scassellati, Social robots as embedded reinforcers of social behavior in children with autism, Journal of autism and developmental disorders 43 (5) (2013) 1038–1049.

[3] H. R. Park, J. M. Lee, H. E. Moon, D. S. Lee, B.-N. Kim, J. Kim, D. G. Kim, S. H. Paek, A short review on the current understanding of autism spectrum disorders, Experimental neurobiology 25 (1) (2016) 1–13.

[4] T. E. Wilens, T. J. Spencer, Understanding attention-deficit/hyperactivity disorder from childhood to adulthood, Postgraduate medicine 122 (5) (2010) 97–109.

[5] R. Charron, Autism rates across the developed world (Sep 2019). URL `https://www.focusforhealth.org/autism-rates-across-the-developed-world/`

[6] J. McCarthy, Artificial intelligence, logic and formalizing common sense, in: Philosophical logic and artificial intelligence, Springer, 1989, pp. 161–190.

[7] J. R. Quinlan, C4. 5: programs for machine learning, Elsevier, 2014.

[8] K. Ashton, et al., That internet of things thing, RFID journal 22 (7) (2009) 97–114.

[9] E. H. Aylward, N. J. Minshew, K. Field, B. Sparks, N. Singh, Effects of age on brain volume and head circumference in autism, Neurology 59 (2) (2002) 175–183.

Journal Pre-proof

Journal Pre-proof

[10] Y. A. Dementieva, D. D. Vance, S. L. Donnelly, L. A. Elston, C. M. Wolpert, S. A. Ravan, G. R. DeLong, R. K. Abramson, H. H. Wright, M. L. Cuccaro, Accelerated head growth in early development of individuals with autism, Pediatric neurology 32 (2) (2005) 102–108.

[11] M. N. HA, A review of serious game for autism children, Computer Games, Multimedia and Allied Technology (CGAT 2012) (2012) 90.

[12] V. Knight, B. R. McKissick, A. Saunders, A review of technology-based interventions to teach academic skills to students with autism spectrum disorder, Journal of autism and developmental disorders 43 (11) (2013) 2628–2648.

[13] N. Kaur, A. Kaur, N. Dhiman, A. Sharma, R. Rana, A systematic analysis of detection of autism spectrum disorder: Iot perspective, International Journal of Innovative Science and Modern Engineering (IJISME) 6.

[14] S. J. Moon, J. Hwang, R. Kana, J. Torous, J. W. Kim, Accuracy of machine learning algorithms for the diagnosis of autism spectrum disorder: Systematic review and meta-analysis of brain magnetic resonance imaging studies, JMIR Mental Health 6 (12) (2019) e14108.

[15] K. K. Hyde, M. N. Novack, N. LaHaye, C. Parlett-Pelleriti, R. Anden, D. R. Dixon, E. Linstead, Applications of supervised machine learning in autism spectrum disorder research: a review, Review Journal of Autism and Developmental Disorders 6 (2) (2019) 128–146.

[16] M. S. Jaliaawala, R. A. Khan, Can autism be catered with artificial intelligence-assisted intervention technology? a comprehensive survey, Artificial Intelligence Review 53 (2) (2020) 1039–1069.

[17] D. Eman, A. W. Emanuel, Machine learning classifiers for autism spectrum disorder: A review, in: 2019 4th International Conference on Information Technology, Information Systems and Electrical Engineering (ICITISEE), IEEE, 2019, pp. 255–260.

Journal Pre-proof

[18] C. Cortes, V. Vapnik, Support-vector networks, Machine learning 20 (3) (1995) 273–297.

[19] S. J. Moon, J. Hwang, H. S. Hill, R. Kervin, K. B. Birtwell, J. Torous, C. J. McDougle, J. W. Kim, Mobile device applications and treatment of autism spectrum disorder: a systematic review and meta-analysis of effectiveness, Archives of Disease in Childhood 105 (5) (2020) 458–462.

[20] M. Jouaiti, P. Henaff, Robot-based motor rehabilitation in autism: A systematic review, International Journal of Social Robotics 11 (5) (2019) 753–764.

[21] M. Abirami, A. S. Banu, T. B. Miranda, M. Dhivya, A systematic review for assisting the echolalia attacked autism people using robot and android application, International Journal of Computer Applications 115 (6).

[22] G. Lorenzo, A. Lled, G. Arrez-Vera, A. Lorenzo-Lled, The application of immersive virtual reality for students with asd: A review between 19902017, Education and Information Technologies 24. doi:10.1007/s10639-018-9766-7.

[23] D.-Y. Song, S. Y. Kim, G. Bong, J. M. Kim, H. J. Yoo, The use of artificial intelligence in screening and diagnosis of autism spectrum disorder: A literature review, Journal of the Korean Academy of Child and Adolescent Psychiatry 30 (4) (2019) 145–152.

[24] Y. Tan, et al., Automatic detection of aortic dissection based on morphology and deep learning, Computers, Materials & Continua 62 (3) (2020) 1201–1215. doi:10.32604/cmc.2020.07127.

[25] M. H. A. Banna, K. A. Taher, M. S. Kaiser, M. Mahmud, M. S. Rahman, A. S. M. S. Hosen, G. H. Cho, Application of artificial intelligence in predicting earthquakes: State-of-the-art and future challenges, IEEE Access 8 (2020) 192880–192923. doi:10.1109/ACCESS.2020.3029859.

Journal Pre-proof

[26] B. Gu, W. Xiong, Z. Bai, Human action recognition based on supervised class-specific dictionary learning with deep convolutional neural network features, Computers, Materials & Continua 63 (1) (2020) 243–262. doi:10.32604/cmc.2020.06898.

[27] M. J. Al Nahian, T. Ghosh, M. H. Al Banna, M. N. Uddin, M. M. Islam, K. A. Taher, M. S. Kaiser, Social group optimized machine-learning based elderly fall detection approach using interdisciplinary time-series features, in: 2021 International Conference on Information and Communication Technology for Sustainable Development (ICICT4SD), 2021, pp. 321–325. doi:10.1109/ICICT4SD50815.2021.9396919.

[28] X. Ma, Y. Lu, Y. Lu, Z. Pei, J. Liu, Biomedical event extraction using a new error detection learning approach based on neural network, CMC-COMPUTERS MATERIALS & CONTINUA 63 (2) (2020) 923–941. doi:10.32604/cmc.2020.07711.

[29] H. Sun, C. Chen, Y. Ling, M. Yang, Cooperative perception optimization based on self-checking machine learning, Computers, Materials & Continua 62 (2) (2020) 747–761. doi:10.32604/cmc.2020.05625.

[30] P. Kalaivaani, R. Thangarajan, Enhancing the classification accuracy in sentiment analysis with computational intelligence using joint sentiment topic detection with medlda, Intelligent Automation & Soft Computing 26 (1) (2020) 71–79. doi:10.31209/2019.100000152.
URL http://www.techscience.com/iasc/v26n1/39857

[31] B. K. Lee, Y. S. Lee, Distinction between real faces and photos by analysis of face data, INTELLIGENT AUTOMATION AND SOFT COMPUTING 26 (1) (2020) 133–139. doi:10.31209/2019.100000134.

[32] T. Lee, K. YOON, D. KANG, S. Seo, Emotion-based painting image display system, INTELLIGENT AUTOMATION AND SOFT COMPUTING 26 (1) (2020) 181–192. doi:10.31209/2019.100000139.

Journal Pre-proof

[33] X. Liu, Y. Si, D. Wang, Lstm neural network for beat classification in ecg identity recognition, Intelligent Automation & Soft Computing 26 (2) (2020) 341–351. doi:10.31209/2019.100000104.
URL http://www.techscience.com/iasc/v26n2/39941

[34] R. Saracoglu, A. F. Kazankaya, Developing an adaptation process for real-coded genetic algorithms, Computer Systems Science and Engineering 35 (1) (2020) 13–19. doi:10.32604/csse.2020.35.013.
URL http://www.techscience.com/csse/v35n1/40057

[35] M. B. Nejad, M. E. Shiri, A new enhanced learning approach to automatic image classification based on salp swarm algorithm, Computer Systems Science and Engineering 34 (2) (2019) 91–100. doi:10.32604/csse.2019.34.091.
URL http://www.techscience.com/csse/v34n2/40030

[36] X. Zhou, K. Li, G. Xiao, Y. Zhou, K. Li, Top k favorite probabilistic products queries, IEEE Transactions on Knowledge and Data Engineering 28 (10) (2016) 2808–2821.

[37] Z. S. Shamma, T. Ghosh, K. A. Taher, M. N. Uddin, M. S. Kaiser, Towards social group optimization and machine learning based diabetes prediction, in: 2021 International Conference on Information and Communication Technology for Sustainable Development (ICICT4SD), 2021, pp. 422–427. doi:10.1109/ICICT4SD50815.2021.9396852.

[38] M. H. A. Banna, T. Ghosh, M. J. A. Nahian, K. A. Taher, M. S. Kaiser, M. Mahmud, M. S. Hossain, K. Andersson, Attention-based bi-directional long-short term memory network for earthquake prediction, IEEE Access 9 (2021) 56589–56603. doi:10.1109/ACCESS.2021.3071400.

[39] H. Zhang, Exploring conditions for the optimality of naive bayes, International Journal of Pattern Recognition and Artificial Intelligence 19 (02) (2005) 183–198.

Journal Pre-proof

[40] M. M. Saritas, A. Yasar, Performance analysis of ann and naive bayes classification algorithm for data classification, International Journal of Intelligent Systems and Applications in Engineering 7 (2) (2019) 88–91.

[41] J. Vaidya, M. Kantarcıoğlu, C. Clifton, Privacy-preserving naive bayes classification, The VLDB Journal 17 (4) (2008) 879–898.

[42] K. Al-Aidaroo, A. Abu Bakar, Z. Othman, Medical data classification with naive bayes approach, Information Technology Journal 11 (2012) 1166–1174. doi:10.3923/itj.2012.1166.1174.

[43] D. Pavithra, A. Jayanthi, R. Nidhya, Comparison of machine learning methods for effective autism diagnosis, in: International Conference on Soft Computing and Signal Processing, Springer, 2019, pp. 629–637.

[44] S. Raj, S. Masood, Analysis and detection of autism spectrum disorder using machine learning techniques, Procedia Computer Science 167 (2020) 994–1004.

[45] J. R. Quinlan, Induction of decision trees, Machine learning 1 (1) (1986) 81–106.

[46] K. S. Omar, P. Mondal, N. S. Khan, M. R. K. Rizvi, M. N. Islam, A machine learning approach to predict autism spectrum disorder, in: 2019 International Conference on Electrical, Computer and Communication Engineering (ECCE), 2019, pp. 1–6.

[47] J. Peral, D. Gil, S. Rotbei, S. Amador, M. Guerrero, H. Moradi, A machine learning and integration based architecture for cognitive disorder detection used for early autism screening, Electronics 9 (3) (2020) 516.

[48] C. Cortes, V. Vapnik, Support-vector networks, in: Machine Learning, 1995, pp. 273–297.

[49] T. S. Furey, N. Cristianini, N. Duffy, D. W. Bednarski, M. Schummer, D. Haussler, Support vector machine classification and validation of cancer

Journal Pre-proof

Journal Pre-proof

tissue samples using microarray expression data, Bioinformatics 16 (10) (2000) 906–914.

[50] A. Tzotsos, D. Argialas, Support vector machine classification for object-based image analysis, in: Object-Based Image Analysis, Springer, 2008, pp. 663–677.

[51] T. Eslami, J. S. Raiker, F. Saeed, Explainable and scalable machine-learning algorithms for detection of autism spectrum disorder using fmri data, arXiv preprint arXiv:2003.01541.

[52] T. H. McCormick, A. E. Raftery, D. Madigan, R. S. Burd, Dynamic logistic regression and dynamic model averaging for binary classification, Biometrics 68 (1) (2012) 23–30.

[53] C. L. Tsien, H. S. F. Fraser, W. J. Long, R. L. Kennedy, Using classification tree and logistic regression methods to diagnose myocardial infarction, Studies in health technology and informatics 52 Pt 1 (1998) 493–7.

[54] M. N. Parikh, H. Li, L. He, Enhancing diagnosis of autism with optimized machine learning models and personal characteristic data, Frontiers in computational neuroscience 13 (2019) 9.

[55] N. S. Altman, An introduction to kernel and nearest-neighbor nonparametric regression, The American Statistician 46 (3) (1992) 175–185. arXiv:https://www.tandfonline.com/doi/pdf/10.1080/00031305.1992.10475879, doi:10.1080/00031305.1992.10475879. URL https://www.tandfonline.com/doi/abs/10.1080/00031305.1992.10475879

[56] B. R. Kowalski, C. Bender, k-nearest neighbor classification rule (pattern recognition) applied to nuclear magnetic resonance spectral interpretation, Analytical Chemistry 44 (8) (1972) 1405–1411.

Journal Pre-proof

[57] M.-L. Zhang, Z.-H. Zhou, A k-nearest neighbor based algorithm for multi-label classification, in: 2005 IEEE international conference on granular computing, Vol. 2, IEEE, 2005, pp. 718–721.

[58] P.-E. Danielsson, Euclidean distance mapping, Computer Graphics and image processing 14 (3) (1980) 227–248.

[59] L.-Y. Hu, M.-W. Huang, S.-W. Ke, C.-F. Tsai, The distance function effect on k-nearest neighbor classification for medical datasets, SpringerPlus 5 (1) (2016) 1–9.

[60] M. J. Al Nahian, T. Ghosh, M. H. Al Banna, M. A. Aseeri, M. N. Uddin, M. R. Ahmed, M. Mahmud, M. S. Kaiser, Towards an accelerometer-based elderly fall detection system using cross-disciplinary time series features, IEEE Access 9 (2021) 39413–39431.

[61] T. K. Ho, Random decision forests, in: Proceedings of 3rd international conference on document analysis and recognition, Vol. 1, IEEE, 1995, pp. 278–282.

[62] A. Liaw, M. Wiener, et al., Classification and regression by randomforest, R news 2 (3) (2002) 18–22.

[63] R. Díaz-Uriarte, S. A. De Andres, Gene selection and classification of microarray data using random forest, BMC bioinformatics 7 (1) (2006) 3.

[64] J. Chen, K. Li, Z. Tang, K. Bilal, S. Yu, C. Weng, K. Li, A parallel random forest algorithm for big data in a spark cloud computing environment, IEEE Transactions on Parallel and Distributed Systems 28 (4) (2016) 919–933.

[65] Z. Zhao, X. Zhang, W. Li, X. Hu, X. Qu, X. Cao, Y. Liu, J. Lu, Applying machine learning to identify autism with restricted kinematic features, IEEE Access 7 (2019) 157614–157622.

Journal Pre-proof

Journal Pre-proof

[66] U. Erkan, D. N. Thanh, Autism spectrum disorder detection with machine learning methods, Current Psychiatry Research and Reviews Formerly: Current Psychiatry Reviews 15 (4) (2019) 297–308.

[67] A. Rouhi, M. Spitale, F. Catania, G. Cosentino, M. Gelsomini, F. Garzotto, Emotify: emotional game for children with autism spectrum disorder based-on machine learning, in: Proceedings of the 24th International Conference on Intelligent User Interfaces: Companion, 2019, pp. 31–32.

[68] J. Ye, R. Janardan, Q. Li, Two-dimensional linear discriminant analysis, in: Advances in neural information processing systems, 2005, pp. 1569–1576.

[69] J. Lu, K. N. Plataniotis, A. N. Venetsanopoulos, Face recognition using lda-based algorithms, IEEE Transactions on Neural networks 14 (1) (2003) 195–200.

[70] Y. Lecun, L. Bottou, Y. Bengio, P. Haffner, Gradient-based learning applied to document recognition, Proceedings of the IEEE 86 (11) (1998) 2278–2324.

[71] B. Khagi, C. G. Lee, G. Kwon, Alzheimers disease classification from brain mri based on transfer learning from cnn, in: 2018 11th Biomedical Engineering International Conference (BMEiCON), 2018, pp. 1–4.

[72] A. Narin, C. Kaya, Z. Pamuk, Automatic detection of coronavirus disease (covid-19) using x-ray images and deep convolutional neural networks, arXiv preprint arXiv:2003.10849.

[73] T. Ghosh, H. Al Banna, N. Mumenin, M. A. Yousuf, et al., Performance analysis of state of the art convolutional neural network architectures in bangla handwritten character recognition, Pattern Recognition and Image Analysis 31 (1) (2021) 60–71.

Journal Pre-proof

Journal Pre-proof

[74] J. Chen, K. Li, K. Bilal, K. Li, S. Y. Philip, et al., A bi-layered parallel training architecture for large-scale convolutional neural networks, IEEE transactions on parallel and distributed systems 30 (5) (2018) 965–976.

[75] M. Duan, K. Li, K. Li, An ensemble cnn2elm for age estimation, IEEE Transactions on Information Forensics and Security 13 (3) (2017) 758–772.

[76] H. Wu, Q. Huang, D. Wang, L. Gao, A cnn-svm combined model for pattern recognition of knee motion using mechanomyography signals, Journal of Electromyography and Kinesiology 42 (2018) 136–142.

[77] M. Afrin, S. Freeda, S. Elakia, P. Kannan, Ai based facial expression recognition for autism children, AI Based Facial Expression Recognition for Autism Children (September 2, 2019). IJETIE 5 (9).

[78] D. E. Rumelhart, G. E. Hinton, R. J. Williams, Learning representations by back-propagating errors, nature 323 (6088) (1986) 533–536.

[79] W.-H. Chen, S.-H. Hsu, H.-P. Shen, Application of svm and ann for intrusion detection, Computers & Operations Research 32 (10) (2005) 2617–2634.

[80] L. E. Achenie, A. Scarpa, R. S. Factor, T. Wang, D. L. Robins, D. S. McCrickard, A machine learning strategy for autism screening in toddlers, Journal of developmental and behavioral pediatrics: JDBP 40 (5) (2019) 369.

[81] M. Duan, K. Li, K. Li, Q. Tian, A novel multi-task tensor correlation neural network for facial attribute prediction, ACM Transactions on Intelligent Systems and Technology (TIST) 12 (1) (2020) 1–22.

[82] M. Duan, K. Li, A. Ouyang, K. N. Win, K. Li, Q. Tian, Egroupnet: a feature-enhanced network for age estimation with novel age group schemes, ACM Transactions on Multimedia Computing, Communications, and Applications (TOMM) 16 (2) (2020) 1–23.

Journal Pre-proof

Journal Pre-proof

[83] A. Ng, et al., Sparse autoencoder, CS294A Lecture notes 72 (2011) (2011) 1–19.

[84] J. Deng, Z. Zhang, E. Marchi, B. Schuller, Sparse autoencoder-based feature transfer learning for speech emotion recognition, in: 2013 Humaine Association Conference on Affective Computing and Intelligent Interaction, IEEE, 2013, pp. 511–516.

[85] M. Che, L. Wang, L. Huang, Z. Jiang, An approach for severity prediction of autism using machine learning, in: 2019 IEEE International Conference on Industrial Engineering and Engineering Management (IEEM), IEEE, 2019, pp. 701–705.

[86] I. W. W. Wisesa, G. Mahardika, Fall detection algorithm based on accelerometer and gyroscope sensor data using recurrent neural networks, in: IOP Conference Series: Earth and Environmental Science, Vol. 258, IOP Publishing, 2019, p. 012035.

[87] M. J. Al Nahian, T. Ghosh, M. N. Uddin, M. M. Islam, M. Mahmud, M. S. Kaiser, Towards artificial intelligence driven emotion aware fall monitoring framework suitable for elderly people with neurological disorder, in: International Conference on Brain Informatics, Springer, 2020, pp. 275–286.

[88] M. Z. Uddin, A wearable sensor-based activity prediction system to facilitate edge computing in smart healthcare system, Journal of Parallel and Distributed Computing 123 (2019) 46–53.

[89] M. Muñoz-Organero, L. Powell, B. Heller, V. Harpin, J. Parker, Using recurrent neural networks to compare movement patterns in adhd and normally developing children based on acceleration signals from the wrist and ankle, Sensors 19 (13) (2019) 2935.

[90] A. Jalal, M. A. K. Quaid, K. Kim, A wrist worn acceleration based human

Journal Pre-proof

motion analysis and classification for ambient smart home system, Journal of Electrical Engineering & Technology 14 (4) (2019) 1733–1739.

[91] A. I. Sumi, M. F. Zohora, M. Mahjabeen, T. J. Faria, M. Mahmud, M. S. Kaiser, fassert: A fuzzy assistive system for children with autism using internet of things, in: International Conference on Brain Informatics, Springer, 2018, pp. 403–412.

[92] V. Khullar, H. P. Singh, M. Bala, Iot based assistive companion for hypersensitive individuals (achi) with autism spectrum disorder, Asian journal of psychiatry 46 (2019) 92–102.

[93] M. H. Al Banna, T. Ghosh, K. A. Taher, M. S. Kaiser, M. Mahmud, A monitoring system for patients of autism spectrum disorder using artificial intelligence, in: International Conference on Brain Informatics, Springer, 2020, pp. 251–262.

[94] H. Nguyen, K. P. Tran, X. Zeng, L. Koehl, G. Tartare, Wearable sensor data based human activity recognition using machine learning: A new approach, arXiv preprint arXiv:1905.03809.

[95] I. Chandra, N. Sivakumar, C. B. Gokulnath, P. Parthasarathy, Iot based fall detection and ambient assisted system for the elderly, Cluster Computing 22 (1) (2019) 2517–2525.

[96] J. Purnama, A. Wijaya, J. Taslim, J. Young, M. Galinium, Facial expression recognition using multiple kinect version 2 cameras, Journal of Physics: Conference Series 1175 (2019) 012077. `doi:10.1088/1742-6596/1175/1/012077`.

[97] S. G. Heng, R. Samad, M. Mustafa, N. R. H. Abdullah, D. Pebrianti, Analysis of performance between kinect v1 and kinect v2 for various facial part movements, in: 2019 IEEE 9th International Conference on System Engineering and Technology (ICSET), 2019, pp. 17–22.

Journal Pre-proof

Journal Pre-proof

[98] M. I. Rusydi, R. Hadelina, O. W. Samuel, A. W. Setiawan, C. Machbub, Facial features extraction based on distance and area of points for expression recognition, in: 2019 4th Asia-Pacific Conference on Intelligent Robot Systems (ACIRS), IEEE, 2019, pp. 211–215.

[99] R. Selkowitz, J. Rodgers, P. Moskal, J. Mrowczynski, C. Colson, Eddie: an embodied ai system for research and intervention for individuals with asd, in: Thirtieth AAAI Conference on Artificial Intelligence, 2016.

[100] T. Y. Tang, P. Winoto, An internet of things approach to read the emotion of children with autism spectrum disorder, Internet of Things A to Z: Technologies and Applications (2018) 563–592.

[101] M. E. Alam, M. S. Kaiser, M. S. Hossain, K. Andersson, An iot-belief rule base smart system to assess autism, in: 2018 4th International Conference on Electrical Engineering and Information & Communication Technology (iCEEiCT), IEEE, 2018, pp. 672–676.

[102] S. F. LeBoeuf, J. B. Tucker, M. E. Aumer, Telemetric apparatus for health and environmental monitoring, uS Patent 8,652,040 (Feb. 18 2014).

[103] S.-g. Roh, H. R. Choi, 3-d tag-based rfid system for recognition of object, IEEE Transactions on Automation Science and Engineering 6 (1) (2008) 55–65.

[104] A. Sula, E. Spaho, K. Matsuo, L. Barolli, F. Xhafa, R. Miho, A new system for supporting children with autism spectrum disorder based on iot and p2p technology, Int. J. of Space-Based and Situated Computing 4 (2014) 55 – 64. `doi:10.1504/IJSSC.2014.060688`.

[105] D. Einarson, P. Sommarlund, F. Segelström, Iot-support systems for parents with adhd an autism, in: 2016 International Conference on Computation System and Information Technology for Sustainable Solutions (CSITSS), IEEE, 2016, pp. 198–203.

Journal Pre-proof

Journal Pre-proof

[106] Q. Wang, Z. Wang, X. Dai, S. Song, T. Xing, S-hrvm: Smart watch-based heart rate variability monitoring system., in: EWSN, 2019, pp. 178–183.

[107] A. M. Al-Kaisey, A. N. Koshy, F. J. Ha, R. Spencer, L. Toner, J. K. Sajeev, A. W. Teh, O. Farouque, H. S. Lim, Accuracy of wrist-worn heart rate monitors for rate control assessment in atrial fibrillation, International Journal of Cardiology 300 (2020) 161–164.

[108] S. Abrar, G. A. Tahir, H. A. Kakudi, C. K. Loo, A personalized blood pressure prediction model using recurrent kernel extreme reservoir machine, in: Future of Information and Communication Conference, Springer, 2019, pp. 913–929.

[109] I. Y. Chung, M. Jung, S. B. Lee, J. W. Lee, Y. R. Park, D. Cho, H. Chung, S. Youn, Y. H. Min, H. J. Park, et al., An assessment of physical activity data collected via a smartphone app and a smart band in breast cancer survivors: Observational study, Journal of medical Internet research 21 (9) (2019) e13463.

[110] C. M. Bertoncelli, P. Altamura, E. R. Vieira, D. Bertoncelli, F. Solla, Using artificial intelligence to identify factors associated with autism spectrum disorder in adolescents with cerebral palsy, Neuropediatrics 50 (03) (2019) 178–187.

[111] F. Thabtah, Autism spectrum disorder screening: machine learning adaptation and dsm-5 fulfillment, in: Proceedings of the 1st International Conference on Medical and health Informatics 2017, 2017, pp. 1–6.

[112] C. Lord, M. Rutter, S. Goode, J. Heemsbergen, H. Jordan, L. Mawhood, E. Schopler, Austism diagnostic observation schedule: A standardized observation of communicative and social behavior, Journal of autism and developmental disorders 19 (2) (1989) 185–212.

[113] F. Thabtah, D. Peebles, A new machine learning model based on induction

Journal Pre-proof

Journal Pre-proof

of rules for autism detection, Health informatics journal 26 (1) (2020) 264–286.

[114] A. S. Halibas, L. B. Reazol, E. G. T. Delvo, J. C. Tibudan, Performance analysis of machine learning classifiers for asd screening, in: 2018 International Conference on Innovation and Intelligence for Informatics, Computing, and Technologies (3ICT), IEEE, 2018, pp. 1–6.

[115] T. Akter, M. S. Satu, M. I. Khan, M. H. Ali, S. Uddin, P. Lio, J. M. Quinn, M. A. Moni, Machine learning-based models for early stage detection of autism spectrum disorders, IEEE Access 7 (2019) 166509–166527.

[116] B. Tyagi, R. Mishra, N. Bajpai, Machine learning techniques to predict autism spectrum disorder, in: 2018 IEEE Punecon, IEEE, 2018, pp. 1–5.

[117] A. A. Abdullah, S. Rijal, S. R. Dash, Evaluation on machine learning algorithms for classification of autism spectrum disorder (asd), in: Journal of Physics: Conference Series, Vol. 1372, IOP Publishing, 2019, p. 012052.

[118] S. A. Elavarasi, J. Jayanthi, N. B. T. Jayasankar, Methods for improving the predictive accuracy of autism spectrum disorder screening using machine learning algorithms, Methods 29 (03) (2020) 9255–9262.

[119] M. Thomas, A. Chandran, Artificial neural network for diagnosing autism spectrum disorder, in: 2018 2nd International Conference on Trends in Electronics and Informatics (ICOEI), 2018, pp. 930–933.

[120] H. Sharif, R. A. Khan, A novel machine learning based framework for detection of autism spectrum disorder (asd), arXiv preprint arXiv:1903.11323.

[121] K. Byeon, J. Kwon, J. Hong, H. Park, Artificial neural network inspired by neuroimaging connectivity: Application in autism spectrum disorder, in: 2020 IEEE International Conference on Big Data and Smart Computing (BigComp), IEEE, 2020, pp. 575–578.

Journal Pre-proof

Journal Pre-proof

[122] R. Tejwani, A. Liska, H. You, J. Reinen, P. Das, Autism classification using brain functional connectivity dynamics and machine learning, arXiv preprint arXiv:1712.08041.

[123] H. Abbas, F. Garberson, S. Liu-Mayo, E. Glover, D. P. Wall, Multi-modular ai approach to streamline autism diagnosis in young children, Scientific reports 10 (1) (2020) 1–8.

[124] D. P. Wall, J. Kosmicki, T. Deluca, E. Harstad, V. A. Fusaro, Use of machine learning to shorten observation-based screening and diagnosis of autism, Translational psychiatry 2 (4) (2012) e100–e100.

[125] D. P. Wall, R. Dally, R. Luyster, J.-Y. Jung, T. F. DeLuca, Use of artificial intelligence to shorten the behavioral diagnosis of autism, PloS one 7 (8).

[126] H. Abbas, F. Garberson, E. Glover, D. P. Wall, Machine learning approach for early detection of autism by combining questionnaire and home video screening, Journal of the American Medical Informatics Association 25 (8) (2018) 1000–1007.

[127] H. Abbas, F. Garberson, E. Glover, D. P. Wall, Machine learning for early detection of autism (and other conditions) using a parental questionnaire and home video screening, in: 2017 IEEE International Conference on Big Data (Big Data), IEEE, 2017, pp. 3558–3561.

[128] J. Kosmicki, V. Sochat, M. Duda, D. Wall, Searching for a minimal set of behaviors for autism detection through feature selection-based machine learning, Translational psychiatry 5 (2) (2015) e514–e514.

[129] S. Levy, M. Duda, N. Haber, D. P. Wall, Sparsifying machine learning models identify stable subsets of predictive features for behavioral detection of autism, Molecular autism 8 (1) (2017) 65.

[130] Q. Tariq, J. Daniels, J. N. Schwartz, P. Washington, H. Kalantarian, D. P. Wall, Mobile detection of autism through machine learning on home video:

Journal Pre-proof

Journal Pre-proof

A development and prospective validation study, PLoS medicine 15 (11) (2018) e1002705.

[131] F. Hauck, N. Kliewer, Machine learning for autism diagnostics: Applying support vector classification, in: Intl Conf. Heal. Informatics Med. Syst., 2017, pp. 120–123.

[132] D. L. Robins, K. Casagrande, M. Barton, C.-M. A. Chen, T. Dumont-Mathieu, D. Fein, Validation of the modified checklist for autism in toddlers, revised with follow-up (m-chat-r/f), Pediatrics 133 (1) (2014) 37–45. arXiv:https://pediatrics.aappublications.org/content/133/1/37.full.pdf, doi:10.1542/peds.2013-1813.
URL https://pediatrics.aappublications.org/content/133/1/37

[133] S. Patra, P. Arun, Use of indian scale for assessment of autism in child guidance clinic: An experience, Indian journal of psychological medicine 33 (2) (2011) 217–219.

[134] E. Schopler, R. J. Reichler, R. F. DeVellis, K. Daly, Toward objective classification of childhood autism: Childhood autism rating scale (cars), Journal of autism and developmental disorders 10 (1) (1980) 91–103.

[135] N. Talebi, A. M. Nasrabadi, I. Mohammad-Rezazadeh, R. Coben, ncreann: Nonlinear causal relationship estimation by artificial neural network; applied for autism connectivity study, IEEE transactions on medical imaging 38 (12) (2019) 2883–2890.

[136] S. Yerramreddy, S. Basu, A. D. Ojha, D. Kalbande, Machine learning approach for diagnosis of autism spectrum disorders, in: International Conference on Innovative Computing and Communications, Springer, 2020, pp. 193–205.

[137] T. Florio, S. Einfeld, B. Tonge, A. Brereton, Providing an independent second opinion for the diagnosis of autism using artificial intelligence over

the internet, Couns, Psycho Health Use Technol Mental Health 5 (2009) 232–248.

[138] S. R. Dutta, S. Datta, M. Roy, Using cogency and machine learning for autism detection from a preliminary symptom, in: 2019 9th International Conference on Cloud Computing, Data Science & Engineering (Confluence), IEEE, 2019, pp. 331–336.

[139] A. Vabalas, E. Gowen, E. Poliakoff, A. J. Casson, Applying machine learning to kinematic and eye movement features of a movement imitation task to predict autism diagnosis, Scientific Reports 10 (1) (2020) 1–13.

[140] V. Yaneva, S. Eraslan, Y. Yesilada, R. Mitkov, et al., Detecting high-functioning autism in adults using eye tracking and machine learning, IEEE Transactions on Neural Systems and Rehabilitation Engineering.

[141] W. Liu, X. Yu, B. Raj, L. Yi, X. Zou, M. Li, Efficient autism spectrum disorder prediction with eye movement: A machine learning framework, in: 2015 International Conference on Affective Computing and Intelligent Interaction (ACII), IEEE, 2015, pp. 649–655.

[142] C. Gillberg, S. Ehlers, H. Schaumann, G. Jakobsson, S. O. Dahlgren, R. Lindblom, A. Bågenholm, T. Tjuus, E. Blidner, Autism under age 3 years: A clinical study of 28 cases referred for autistic symptoms in infancy, Journal of Child Psychology and Psychiatry 31 (6) (1990) 921–934.

[143] E. Marchi, B. Schuller, A. Baird, S. Baron-Cohen, A. Lassalle, H. OReilly, D. Pigat, P. Robinson, I. Davies, T. Baltruaitis, A. Adams, M. Mahmoud, O. Golan, S. Fridenson-Hayo, S. Tal, S. Newman, N. Meir-Goren, A. Camurri, S. Piana, S. Blte, M. Sezgin, N. Alyuz, A. Rynkiewicz, A. Baranger, The asc-inclusion perceptual serious gaming platform for autistic children, IEEE Transactions on Games 11 (4) (2019) 328–339.

Journal Pre-proof

Journal Pre-proof

[144] M. Rogli, V. Bobi, M. Djuri-Jovii, M. Djordjevi, N. Dragaevi, B. Nikoli, Serious gaming based on kinect technology for autistic children in serbia, in: 2016 13th Symposium on Neural Networks and Applications (NEUREL), 2016, pp. 1–4.

[145] A. Sula, E. Spaho, K. Matsuo, L. Barolli, R. Miho, F. Xhafa, An iot-based system for supporting children with autism spectrum disorder, in: 2013 Eighth International Conference on Broadband and Wireless Computing, Communication and Applications, IEEE, 2013, pp. 282–289.

[146] V. S. Amante, C. R. Jeryl de Vera, J. L. Anne Espinosa, S. P. Pamela Reyes, G. Agregado, AIDISM: An Android-based Game to Educate Individuals with Autism on Basic First Aid using Artificial Intelligence, International Journal of Conceptions on Computing and Information Technology 3 (3) (2015) 2345–9808.

[147] S. Veeraraghavan, K. Srinivasan, Exploration of autism using artificial intelligence techniques, in: HEALTHCOM 2006 8th International Conference on e-Health Networking, Applications and Services, IEEE, 2006, pp. 180–183.

[148] A. Sula, E. Spaho, K. Matsuo, L. Barolli, F. Xhafa, R. Miho, An iot-based framework for supporting children with autism spectrum disorder, in: Information Technology Convergence, Springer, 2013, pp. 193–202.

[149] A. M. Radwan, B. Birkan, F. Hania, Z. Cataltepe, Active machine learning framework for teaching object recognition skills to children with autism, International Journal of Developmental Disabilities 63 (3) (2017) 158–169.

[150] O. Rudovic, J. Lee, M. Dai, B. Schuller, R. W. Picard, Personalized machine learning for robot perception of affect and engagement in autism therapy, Science Robotics 3 (19).

[151] G. Palestra, B. De Carolis, F. Esposito, Artificial intelligence for robot-assisted treatment of autism., in: WAIAH@ AI* IA, 2017, pp. 17–24.

Journal Pre-proof

[152] B. Kinsella, 46.3 artificial intelligence: Utilizing google glass and other mobile applications for social skills training in autism spectrum disorders, Journal of the American Academy of Child & Adolescent Psychiatry 10 (55) (2016) S70–S71.

[153] Y. Shi, S. Das, S. Douglas, S. Biswas, An experimental wearable iot for data-driven management of autism, in: 2017 9th International Conference on Communication Systems and Networks (COMSNETS), 2017, pp. 468–471.

[154] M. I. Mamun, A. Rahman, M. A. Khaleque, M. A. Hamid, M. F. Mridha, Autilife: A healthcare monitoring system for autism center in 5g cellular network using machine learning approach, in: 2019 IEEE 17th International Conference on Industrial Informatics (INDIN), Vol. 1, IEEE, 2019, pp. 1501–1506.

[155] A. J. Masino, D. Forsyth, H. Nuske, J. Herrington, J. Pennington, Y. Kushleyeva, C. P. Bonafide, m-health and autism: Recognizing stress and anxiety with machine learning and wearables data, in: 2019 IEEE 32nd International Symposium on Computer-Based Medical Systems (CBMS), IEEE, 2019, pp. 714–719.

[156] T. Y. Tang, P. Winoto, An interactive picture exchange communication system (pecs) embedded with augmented aids enabled by iot and sensing technologies for chinese individuals with autism, in: Proceedings of the 2018 ACM International Joint Conference and 2018 International Symposium on Pervasive and Ubiquitous Computing and Wearable Computers, 2018, pp. 299–302.

[157] M. Becherer, M. Zipperle, A. Karduck, Intelligent choice of machine learning methods for predictive maintenance of intelligent machines, Computer Systems Science and Engineering 35 (2) (2020) 81–89. doi:10.32604/csse.2020.35.081.
URL http://www.techscience.com/csse/v35n2/40062

Journal Pre-proof

Journal Pre-proof

[158] V. S. Naresh, S. S. Pericherla, P. S. R. Murty, S. Reddi, Internet of things in healthcare: Architecture, applications, challenges, and solutions, Computer Systems Science and Engineering 35 (6) (2020) 411–421. doi:10.32604/csse.2020.35.411.
URL http://www.techscience.com/csse/v35n6/40719

[159] V. S. Sheng, Y. Shen, L. Wang, W. Fang, X. Xi, D. Zhang, Empirical comparisons of deep learning networks on liver segmentation, Computers, Materials & Continua 62 (3) (2020) 1233–1247. doi:10.32604/cmc.2020.07450.

[160] B. Janakiraman, S. Arumugam, Personalized nutrition recommendation for diabetic patients using optimization techniques, Intelligent Automation & Soft Computing 26 (2) (2020) 269–280. doi:10.31209/2019.100000150.
URL http://www.techscience.com/iasc/v26n2/39944

[161] Y. Min, X. Fengxiang, W. Junhao, Z. Xuefeng, Injury analysis of vehicle-pedestrian collision based on orthogonal experiments, Computer Systems Science and Engineering 35 (3) (2020) 173–181. doi:10.32604/csse.2020.35.173.
URL http://www.techscience.com/csse/v35n3/40087

[162] K. He, X. Zhang, S. Ren, J. Sun, Deep residual learning for image recognition, in: The IEEE Conference on Computer Vision and Pattern Recognition (CVPR), 2016.

[163] C. Szegedy, W. Liu, Y. Jia, P. Sermanet, S. Reed, D. Anguelov, D. Erhan, V. Vanhoucke, A. Rabinovich, Going deeper with convolutions, in: The IEEE Conference on Computer Vision and Pattern Recognition (CVPR), 2015.

[164] M. Sandler, A. Howard, M. Zhu, A. Zhmoginov, L.-C. Chen, Mobilenetv2: Inverted residuals and linear bottlenecks, in: The IEEE Conference on Computer Vision and Pattern Recognition (CVPR), 2018.

Journal Pre-proof

Journal Pre-proof

[165] T. Ghosh, M. M.-H.-Z. Abedin, S. M. Chowdhury, Z. Tasnim, T. Karim, S. S. Reza, S. Saika, M. A. Yousuf, Bangla handwritten character recognition using mobilenet v1 architecture, Bulletin of Electrical Engineering and Informatics 9 (6) (2020) 2547–2554.

[166] K. Simonyan, A. Zisserman, Very deep convolutional networks for large-scale image recognition, CoRR abs/1409.1556.

[167] C. Chen, K. Li, A. Ouyang, Z. Tang, K. Li, Gpu-accelerated parallel hierarchical extreme learning machine on flink for big data, IEEE Transactions on Systems, Man, and Cybernetics: Systems 47 (10) (2017) 2740–2753. doi:10.1109/TSMC.2017.2690673.

[168] M. Duan, K. Li, X. Liao, K. Li, A parallel multiclassification algorithm for big data using an extreme learning machine, IEEE transactions on neural networks and learning systems 29 (6) (2017) 2337–2351.

[169] K. Li, W. Ai, Z. Tang, F. Zhang, L. Jiang, K. Li, K. Hwang, Hadoop recognition of biomedical named entity using conditional random fields, IEEE Transactions on Parallel and Distributed Systems 26 (11) (2014) 3040–3051.

[170] X. Zhou, K. Li, Y. Zhou, K. Li, Adaptive processing for distributed skyline queries over uncertain data, IEEE Transactions on Knowledge and Data Engineering 28 (2) (2016) 371–384. doi:10.1109/TKDE.2015.2475764.

[171] S. Singh, P. K. Sharma, B. Yoon, M. Shojafar, G. H. Cho, I.-H. Ra, Convergence of blockchain and artificial intelligence in iot network for the sustainable smart city, Sustainable Cities and Society 63 (2020) 102364. doi:https://doi.org/10.1016/j.scs.2020.102364. URL https://www.sciencedirect.com/science/article/pii/S2210670720305850

[172] P. K. Sharma, J. H. Park, K. Cho, Blockchain and federated learning-based distributed computing defence framework for sustainable society,

Sustainable Cities and Society 59, this research was supported by BK21 Plus project of the National Research Foundation of Korea Grant and was supported by the Dongguk University Research Fund of 2020. doi:10.1016/j.scs.2020.102220.

[173] S. Hochreiter, J. Schmidhuber, Long short-term memory, Neural computation 9 (1997) 1735–80. doi:10.1162/neco.1997.9.8.1735.

[174] J. Chung, Ç. Gülçehre, K. Cho, Y. Bengio, Empirical evaluation of gated recurrent neural networks on sequence modeling, CoRR abs/1412.3555. arXiv:1412.3555.
URL http://arxiv.org/abs/1412.3555

Journal Pre-proof

Journal Pre-proof

Abbreviations

ABIDE	Autism Brain Imaging Data Exchange
ADHD	Attention Deficit Hyperactivity Disorder
ADI-R	The Autism Diagnostic Interview-Revised
ADOS	Autism Diagnostic Observation Schedule
AI	Artificial Intelligence
ANN	Artificial Neural Network
AQ-10	Autism Spectrum Quotient
ASD	Autism Spectram Disorder
BRB	Belief Rule Based
CARS	Childhood autism rating scales
CNN	Convolutional Neural Network
DL	Deep Learning
DT	Decision Tree
FAU	Facial action unit
FES	Fuzzy expert system
GLCM	Grey Level Co-occurrence Matrix
GPS	Global Positioning System
IoT	Internet of Things
KNN	K Nearest Neighbor
LDA	Linear Discriminant Analysis
LR	Logistic Regression
ML	Machine Learning
mRMR	Minimum Redundancy and Maximum Relevance
NB	Nave Bayes
NDAR	National dataset for autism research
NN	Neural Network
RF	Random Forest
RFID	Radio Frequency Identification
RKF	restricted kinematic features
RL	Reinforcement Learning
RML	rule-based Machile Learning
RML	Rule-based ML
RNN	Recurrent Neural Network
RNN	Recurrent Neural Network
SVM	Support Vector Machine

Journal Pre-proof

Journal Pre-proof

COMPLIANCE WITH ETHICAL STANDARDS

Conflicts of Interest: All authors declare that they have no conflict of interest.

Ethical Approval: No ethical approval required for this study.

Informed Consent: This study used secondary data. Therefore, the informed consent does not apply.

Authors and Contributors: This work was carried out in close collaboration between all co-authors.

Journal Pre-proof