Role of Hidden Markov Models in Autism Prediction, Diagnosis and Therapy

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***Abstract*—Autism is a developmental disability due to alterations in the brain. People having ASD display repetitive behavior, problems in social interaction and communication issues. Hidden markov are a special type of two process markov chain that have applications stretching in all spheres. The importance of use of HMMs lies in the fact that early diagnosis and treatment is the crucial to prevent the condition from escalating. However, the conventional methods requires a therapist and are expensive, time consuming and inconvenient for both the children and parents. Hence, our paper aims to explore and summarize the existing literature to provide a holistic view of efforts done to make predictions and estimates about autism, diagnose autistic people, and identify and understand causes linked to ASD using Hidden Markov Models. For each purpose, our work presents state-of-the-art approaches which are efficient in fulfilling the need. This survey contributes toward employability of Hidden Markov Models for prediction, diagnosis and in-depth study of autism spectrum disorder and its causes.**

***Index Terms*—autism, ASD, markovchains, HMMs, Stochastic processes**

I. Introduction

Autism is a complex neurodevelopmental disorder that affects communication and social interaction. While the exact causes of autism are not yet fully understood, research suggests that it may involve both genetic and environmental factors. Regardless of the cause, early diagnosis of autism is very important because it allows for early intervention and treatment, which can greatly improve the outcomes for individuals with autism. Without early diagnosis, individuals with autism may not receive the support and resources they need to reach their full potential. Unfortunately, not everyone has access to affordable ways to diagnose autism. This can be a barrier for many families, especially those who do not have insurance or access to specialized clinics. Novel ways are being to explore the issue and non clinical and data driven approaches are being used for its diagnosis and study. In recent years, hidden Markov models (HMMs) have been proposed as a potential tool for studying autism and other neurodevelopmental disorders. HMMs are a type of mathematical model that can be used to analyze complex time-series data, such as the brain activity measured by electroencephalography (EEG) or functional magnetic resonance imaging (fMRI). By using HMMs to analyze this type of data, researchers may be able to identify patterns and features that are unique to autism and other neuro-developmental disorders, which could provide valuable insights into the underlying causes and mechanisms of these disorders. We have based our survey on three main papers from the literature review. The first paper aims to shed light on estimating the probability of having autistic children for parents beforehand. The authors have used statistical data to designed the model and simulated parent profiles to test the results. The second approach focuses on understanding the causes and connection of brain activity with autism using HMMs whereby fMRI data of ASD and Health Control Subjects is used to investigate brain states corresponding cognitive functions of the brain. The third and last approach focuses on diagnosing ASD level- mild or minimal using observations obtained from interaction of subjects with NAO robots. Next the paper will briefly discuss other literature that applies HMMs to autism followed by the research challenges observed in each study.

II. Terminology

A. Autism Spectrum Disorder

Autism Spectrum Disorder(ASD) commonly abbreviated as Autism is a neuro-development disorder that is surfaced among children in their infancy. Rather than having fixed symtoms, as the name implies, the disorder has a spectrum that overlaps with normality on one end and impairment on the other. Common issues with ASD people include repetition, no tolerance to out of order things, communication issues, difficulty to understand and process emotions of their selves and others.

B. Hidden Markov Models

Hidden Markov Models are a specific type of double layered Markov Process that are specially suited to obtaining probabilities of phenomena where although the certain states are not directly observable, they emit other states/results which are observable [1]. Such phenomena are all around us. If one is to consider autism, it could be best modeled by an HMM where the unobservable state is the diagnosis or non-diagnosis and the observed states are behavioral, speech, facial and gaze patterns. There are other possible ways of modeling Autism with HMMs which will be further explored in the paper.

HMMs are derived from Markov processes which are stochastic processes where the future only depends on the present and is independent of the past.

$$P[X_{n+1}|X_n, X_{n-1}, X_{n-2}....X_0] = P[X_{n+1}|X_n]$$

Thus, a Markov process is a mathematical system that undergoes transitions from one state to another according to certain probabilistic rules. In other words, it is a sequence of random events in which the probability of each event depends only on the state attained in the previous event. [1]

These Markov processes are the underlying mechanism in hidden markov models. A hidden markov model can be defined as $\lambda(\pi, A, B)$ with N states an M observations where

- π is the initial state probability vector $\pi = \pi_i$ where $0 < \pi_i \leq 1, 0 \leq i \leq N$ and $\Sigma_{i=0}^{N-1}\pi_i = 1$
- A is the probability transition matrix of the hidden states in the unobservable model. $A = \{a_{ij}\}$ where $a_{ij} > 0, 0 \leq i, j < N$ and $\Sigma_{j=0}^{N-1} a_{ij} = 1, \forall 0 \leq i < N$
- B is the emission probability matrix consisting of probabilities of hidden states emitting certain observation. $B = b_j(k)$ where $b_j(k) > 0, 0 \leq k < M$ and $\Sigma_{k=0}^{M-1} b_j(k) = 1 \forall 0 \leq j < N$

In addition to the above entities, HMMs operate under certain assumptions necessary to impose the markov structure.

- The next state only depends on the current state. $a_{ij} = P[q_{t+1}|q_t]$
- time here is independent of the start time t_0 i.e, $P[q_{t_1+1} = j|q_{t_1} = i] = q_{t_2+1} = j|q_{t_2} = i]$
- Any output observation occuring at time t only depends on the state q_t and is independent of any other observation. Therefore if $O = o_1 o_2 o_3..o_T$ then $P[O|q_1 q_2 q_3 q_t, \lambda] = \Pi_{t=1}^{T} P[o_t|q_t, \lambda]$

Hidden Markov models (HMMs) have applications stretching across different domains. Any process having an unobservable state mechanism but observable indications can be modelled by an HMM. HMMs prominent applications include automatic speech recognition, weather forecasting, signal processing, genetics and computational biology [1]. Specific to our paper, HMMs also have been used for modeling several different problems in medical researches , including approaches to diagnose cancer, for genotype imputation and to investigate heart abnormalities [2].

III. Recent Approaches in Direction of Autism

There is a wide variety of recommendation approaches presented in the literature surrounding autism and hidden markov models. In this paper, we will explore three such approaches which shed light on prediction, study and diagnosis of autism using Hidden Markov models.

A. Estimation of autism heritability using HMMs through statistical data

HMMs have been employed in unique ways to predict estimates related to autism. One of our primary paper 'Hidden Markov Models to Estimate the Probability of Having Autistic Children' uses statistical data to develop a Hidden markov model and test it on a simulated set of parents [2]. Here we will explore in more detail the methodology and results obtained in this study.

1) Methodology: Statistical data of ASD heritability and ASD sibling recurrence was used to model the phenomena of Autism heritibility in children using a Hidden Markov Model [2]. The use of Hidden Markov Models (HMMs) was deemed appropriate for this study due to their ability to generate probabilities based on prior knowledge of the states being considered. This aligns well with the statistical nature of the available data on the heritability and recurrence of ASD, making HMMs a transparent and straightforward starting point for the investigation. Since the child is unborn, their diagnosis is a hidden state. On the contrary, since the clinical diagnosis or genetic characterstics of parent is an observable condition, they are part of the observable MC. Thus, states were defined in the following manner. The hidden MC had two states: TD (Typical Girl or Boy) and ASD (ASD Girl or Boy). The model consisted of two observations" TP(Typical Parent) and AP(Autistic Parent). Next, the initial state probability vector was modelled using ASD prevalance data source. The children general ASD prevalence, regardless of gender is P(ASD) = 0.0125; the ASD prevalence among girls is P(AG) = 0.005; and the ASD prevalence among boys is P(AB) = 0.0197. Thus two different initial state vectors were designed for boys and girls as follows.

$$\pi = \begin{array}{cc} TD & ASD \\ \end{array}$$
$$\pi = \begin{pmatrix} 1 - P(ASD) & P(ASD) \end{pmatrix}$$

$$\begin{array}{cc} TD & ASD \end{array}$$
$$\pi\mathbf{G} = \begin{pmatrix} 0.995 & 0.005 \end{pmatrix}$$

$$\begin{array}{cc} TD & ASD \end{array}$$
$$\pi\mathbf{B} = \begin{pmatrix} 0.9803 & 0.0197 \end{pmatrix}$$

Similarly, transition probability matrix has been modelled using the ASD sibling recurrence data. In cases where the older sibling is male, the likelihood of a younger sibling being diagnosed with ASD was found to be 4.2% for females and 12.9% for males. When the older sibling is female, the likelihood increased to 7.6% for younger female siblings and 16.8% for younger male siblings [2]. Similar statistics were obtained when the older sibling is a typical child. Three transition matrices were designed for each gender since the probabilities significantly changed according to the gender of the older sibling – Two of them were according to the older sibling gender, and the other one disregarding the older sibling gender entirely. A sample transition matrix for birth of females is given below.

$$\mathbf{A(MF)} = \begin{array}{c} \\ TB \\ AB \end{array} \begin{array}{c} \begin{array}{cc} TG & AG \end{array} \\ \begin{pmatrix} P(TG|TB) & P(AG|TB) \\ P(TG|AB) & P(AG|AB) \end{pmatrix} \end{array}$$

$$\mathbf{A(MF)} = \begin{array}{c} \\ TB \\ AB \end{array} \begin{array}{c} \begin{array}{cc} TG & AG \end{array} \\ \begin{pmatrix} 0.9962 & 0.0038 \\ 0.9578 & 0.0422 \end{pmatrix} \end{array}$$

The last element left in the HMMs is the emission probabilities. The same but extended ASD diagnosis and heritability data used in initial state probability vector was used to model emission probability matrix. They defined two emission matrices, one for boys (B(B)) and one for girls (B(G)). B(B) has been given below [2].

$$\mathbf{B}(\mathbf{B}) = \begin{array}{c c} & \begin{array}{cc} TP & AP \end{array} \\ \begin{array}{c} TB \\ AB \end{array} & \begin{pmatrix} 1 - P(AP|TB) & P(AP|TB) \\ 1 - P(TP|AB) & P(AP|AB) \end{pmatrix} \end{array}$$

These all can be best summarized by the following diagram [2]

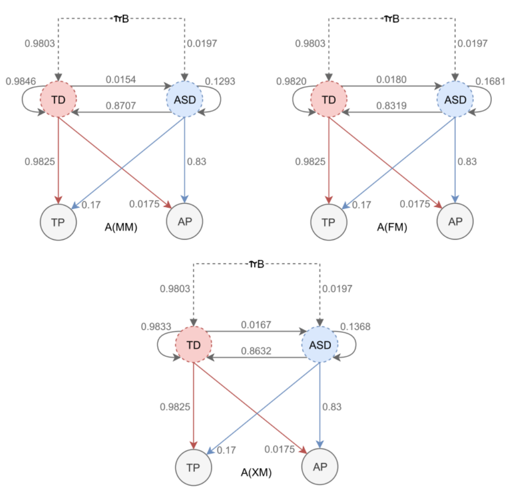

Fig. 1. HMMs for predicting the probability of having ASD boys. A(MM)

2) Experimentation: To design the model, hmmlearn, an open source python library was used. Authors of the paper created simulated children based on the states of two different parents. These states, known as parent profiles, were used to model our observable states. For each set of hidden Markov models (one for boys and one for girls) and each combination of parent states, birth of two children was simulated. For testing and evaluation on this data, predict_proba method with viterbi as the algorithm was used.

3) Results: The essential results obtained from different parent profiles(Typical and Autistic) are summarized in the figure below.

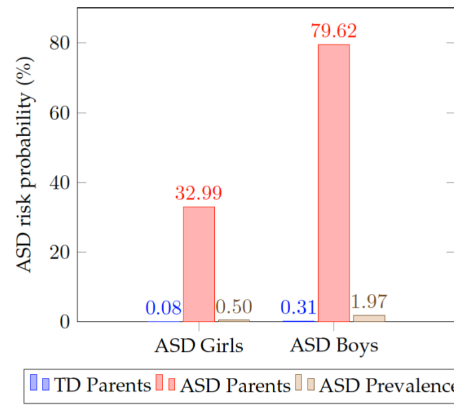

Fig. 2. HMMs for predicting the probability of having ASD boys. A(MM) [2]

These results indicated that HMMs do a decent job in conveying the risk of having ASD children among TD and ASD parents and the predicted probabilities are coherent with the results from literature. we estimated that ASD parents could give birth to ASD children with probabilities of around 33% for girls and around 80% for boys. This was the first and one of a kind attempt to uses genetic data for prediction of ASD Diagnosis. This was one of a kind study which would evolve over time with the availability of new ASD data.

B. Causal exploration of brain network dynamics in ASD people using HMMs

Research suggests that abnormal brain responses may be a contributing factor to the development of autism [3]. Some theories propose that changes in functional or structural brain networks may play a role in the condition. Some functional MRI studies have highlighted reduced functional connectivity between sensory and default mode networks as a potential cause of autism. Most of the existing literature on the subject assumes that resting state fMRI reflects stable brain activity, but this research suggests that the brain can be modeled as a dynamic system that transitions between different states associated with different cognitive functions [3]. Due to sliding window approach for dynamic Functional Connectivity Analysis being limited, this study explores the use of Hidden Markov model to capture brain states from time series data.

1) Methodology: Data in the form of fMRI scan images were collected from 507 males out of which 209 had ASD while others had typical development [3]. Resting state functional magnetic resonance imaging (FMRI) is a type of brain imaging that is used to measure the activity of the brain at rest. This type of imaging is typically used to study the intrinsic functional connectivity of the brain, which refers to the way in which different brain regions work together to perform various functions. It was ensured through curation and normalization that all of the data samples had similar characteristics including FIQ(full IQ), FID, age etc. Pre-processing involved removing first 10 images, normalization, correcting head motion, regressing noise from fluids and performing spatial smoothing. These were carried out using the Statistical Parameter Mapping 8 (SPM8) and the Data Processing Assistant for Resting-State fMRI (DPARSF) toolbox.

The primary hypothesis of this research was that brain activity can be classified into discrete mutually exclusive recurring states which can be modelled by a Hidden Markov Model. The states themselves are abstract and unobservable however they can be predicted though observations from the f-MRI data. The study obtained the average time courses of 90 different regions of interest (ROIs) in the brains of all subjects and adjusted them by dividing them by their standard deviation [3]. The time courses from each ROI were then combined across all participants to create a data matrix. Dimensionality reduction was also performed using principal component analysis to reduce from 90 ROIs to just 32 thus preventing overfitting. The following figure shows a visual description of the problem.

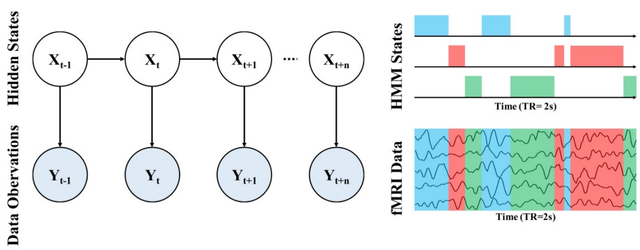

Fig. 3. Schematic illustration of the whole-brain dynamics using a Hidden Markov Model (HMM). [3]

2) Experimentation: Before training the hidden markov model on the 209 ASD subjects and 298 HCs, the number of states had to be decided because it is a free parameter and different numbers manage to capture different levels of details. Free energy and median fractional occupancy were used as global statistics to find the optimal number of states [3]. Free energy did not indicate any meaningful results. On the other hand, the median fractional occupancy decreased rapidly for the smaller number of states and stopped at 19th state, hence 19 was decided to be the total number of hidden states in the HMM. Further experiments were performed on the inferred HMM whose results will be shared in the next section. From the inferred HMM, the Bayesian inference method was used to generate a time series of probabilities that represented the likelihood of each state being active at a given time [3]. These probabilities were utilized to calculate global statistics that reflect the properties and dynamics of the HMM states namely including fractional occupancies, lifetime, and interval time. Upon the inferred model and transition probabilities, further experimentation was performed to obtain modularity maximization through network-based clustering or community detection technique.

3) Results: With 19 states chosen as the free parameter, the hidden markov model was able to identify 19 Hidden states considerably well. To study how the brain network changes over time in ASD, global temporal characteristics of the HMM states were calculated and compared including how often they are occupied(fractional times), how long they last(lifetime), and how much time passes between them(interval time). The figure below gives a comparison of just one temporal characteristic - Fractional Occupancy in ASD subjects and Health controls.

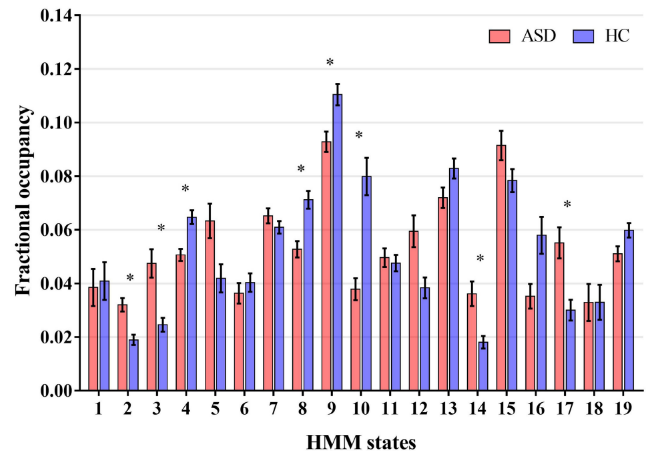

Fig. 4. Alteration of the global temporal characterizes in autism spectrum disorder (ASD) [3]

The transition probability matrix obtained through the inferred HMM was analyzed using modularity analysis. Under the analysis, transition matrix of the HMM states for subjects with ASD and HCs was organized into a specific community structure with three partitions. The three modules were identified as the HC-related module and the two ASD-related modules [3]. The HC-related module was characterized by HMM states 4, 8, 9, and 10, which showed significantly higher fractional occupancies and lifetimes in HCs. The ASD-related modules were identified as module I, which included HMM states 2 and 17, and module II, which included HMM states 3 and 14. longer fractional occupancies and lifetimes were observed in subjects with ASD [3]. Following figure shows the transition matrix maps and the corresponding modules.

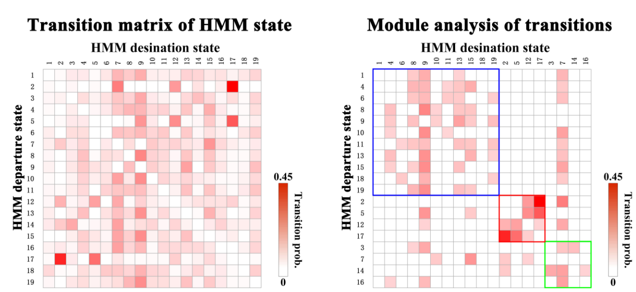

Fig. 5. The modules of transitions between HMM states [3]

This research also examined the spatial activation map of whole brain states in the HC and ASD modules. These provided visual indicators of under-connectivity and over-connectivity of different ROIs in thhe brain as well as abnormalities in the subnetworks of the brain. Specifically, it was observed that in the ASD-related module II, two HMM states showed opposite trends of activation in the default mode network (DMN). State 3 showed an increase in DMN activation, including in the ACC and the superior and medial frontal gyrus, while state 14 showed a decrease in these areas. Similar peculiarities were observed in ASD-related module II which could provide insights to neuroscientists on ASD and brain activity.

C. Categorization of ASD Level using HMMs

With the prediction of autism, categorization of the severity of autism is also critical. Autism can be categorized into three different levels ranging from mild to severe. An approach given by [4] focuses on the prediction of level of autism in children. The main aim of the work was to categorize the level 1, minimal and level 2, mild categories of autism using the Multi-robot-mediated intervention system (MRIS) and Hidden Markov Models (HMMs). The motivation behind this work is that the conventional method for the diagnosis of the level of autism includes a therapist. The therapist analyzes the behaviour of child and categorizes according to autism rating scale. The therapies for the child were recommended. However, such therapies are expensive, hence technology is being used nowadays for the therapy for ASD children. Robot mediated therapy is a recent development for the therapeutic interventions. This is advantageous as children with ASD may are more comfortable with robots more frequently and interact more with them as compare to humans. However, there wasn't any robot mediated system which can categorize the level of autism by analyzing the behavior of autism before this research. The paper focuses on two impairments of ASD Children: Attention and Imitation and based on their performance in these two, level of autism is diagnosed using HMMs. Attention is analyzed using Joint Attention module where the attention of the ASD Child was analyzed using his gaze. Imitation model was used to analyze child's learning, focus and interaction. The levels of autism were the observable states and that was deduced using unobservable states which included joint attention and imitation.

1) Methodology: As it's a multi-robot therapy, two NAO humanoid robots are used for each module. As discussed system uses two models, MRIS and HMMs. MRIS is used to measure joint attention and imitation whereas HMM predicts the category of autism using the results of the success rate in the JA and IM models. The setup is of a triad human communication where the two NAO humanoid robots are kept at 1 meter distance from the child. For the JA module, one of the robots gives cues to gain the attention of the child. The cues were the combination of three types, visual, speech and motion. For the visual cue, the robot changes eye color (known as "*Rasta*") or blinks. For the speech, the robot says "Hi" or "Hello". Lastly, for the motion cue, the robot moves forward, backwards, stands up or down. The IM module was activated only when child maintains eye contact with the robot. Hence in JA module, the gaze of child was analyzed i.e. if the child is looking at robot, the interval before making the eye contact, and the time period for which the contact is maintained. For this statistical analysis of gaze labelling, *NaoqiPeoplesPerception* of Naoqi SDK is used which uses data from the cameras of NAO robots to infer results. After the imitation module is activated, the robot performs imitation tasks using NAO API, which includes moving forward, moving backward, lifting hands up and down. The child mimics the gestures done by robots and the movements of child is measured using Kinect sensors. The sensors uses joint movements of the child to compare the robot gestures and child's imitations and then success rate was calculated. After this, the HMM categorizes the level of autism using the performance in the two modules. The performance in each module is further categorized into three. This can be seen in Table I. The categories were decided by the consultation of therapist. The HMM architecture is shown in Figure 6 and it's probabilities are shown in Figure 7. The probabilities were found by training the model.

TABLE I
CATEGORY AND PERCENTAGE OF SUCCESS

Parameter	Category	Percentage of Success(%)
Joint Attention	Low	≤ 50
	Delayed	$> 50$and < 80
	Immediate	$\geq 80$and ≤ 100
Imitation	Partial	≤ 50
	Moderate	$> 50$and < 80
	Full	$\geq 80$and ≤ 100

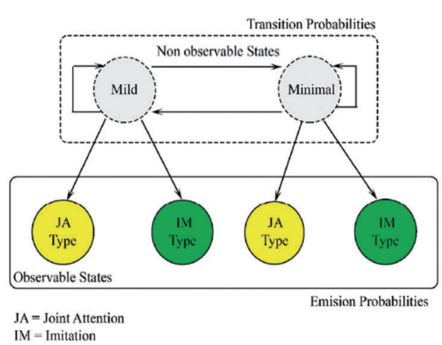

Fig. 6. HMM-Based System Architecture Explaining Observable and NonObservable States

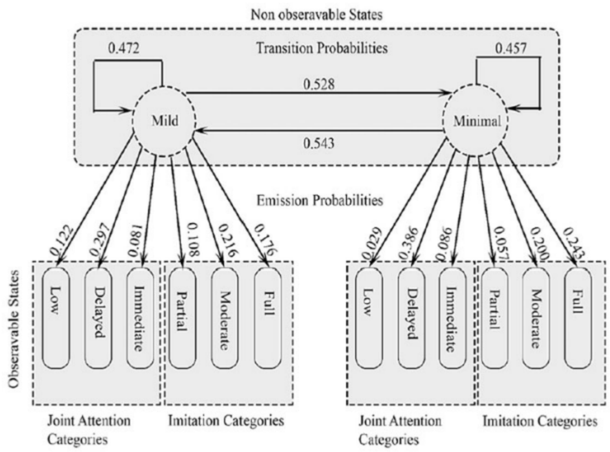

Fig. 7. HMM-Based with probabilities

The updated probabilities i.e. the posterior probabilities were calculated using equations 1, 2 and 3.

$$P(\text{Category} = \text{Mild}) = 0.472 \times \text{Mild} + 0.543 \times \text{Minimal} \quad (1)$$

$$P(\text{Category} = \text{Minimal}) = 0.472 \times \text{Minimal} + 0.543 \times \text{Mild} \quad (2)$$

$$P(\text{Category} = \text{Mild}) + P(\text{Category} = \text{Minimal}) = 1 \quad (3)$$

The probability of a category given the performance of modules is calculated using equation 4.

$$P(\text{Category} = \text{level of autism})|\text{JA=category, IM=category}) \quad (4)$$

For instance, probability that a child has Mild level of autism given that Joint Attention category is immediate and Imitation category is full is as follows:

$$P(\text{Category} = \text{Mild})|\text{JA=immediate, IM=full}) \quad (5)$$

Hence,

$$= P(\text{Category=Mild—JA=immediate}) \times P(\text{Category=Mild—IM=full}) \quad (6)$$

where

$$P(\text{Category} = \text{Mild})|\text{JA=immediate}) = \frac{P(JA_{immediate} \cap \text{Category}_{Mild})}{P(JA_{immediate})} \quad (7)$$

and

$$P(\text{Category} = \text{Mild})|\text{IM=full}) = \frac{P(IM_{full} \cap \text{Category}_{Mild})}{P(IM_{full})} \quad (8)$$

Using above probabilities, the HMM predicts the level of autism.

2) Experiment: The experiment was performed on 12 subjects where 8 children were part of the training of Hidden Markov Models and rest were part of testing. 72 and 25 experiments were performed for training and testing respectively.

3) Results and Discussion: The average performance in joint attention and imitation module was 65.47 percent and 76.19 percent respectively. The testing accuracy was 76 percent i.e. 19 out of 25 samples were correct. The importance of this work is that it's the first prediction model and that uses robot mediated therapy for diagnosis level of autism. Moreover, since accuracy is 76 percent, the proposed approach is reliable. Other than that, the system uses a triad human communication scenario i.e. 2 robots and a human without any human intervention. This saves cost that is needed for the diagnosis. Lastly, the work performs statistical analysis for gaze labelling using NAO library i.e the robot itself analyzes the gaze whereas previously it was done manually. Hence, this is an efficient way to get good accuracy, save cost and create an environment according to the comfort of children.

D. Others

The work done in connecting autism with Hidden Markov models is not just limited to the above three approaches. Some of the studies have not been mentioned in detail for the sake of brevity.

Another literature attempts to recognize stereotyped gesture recognition in Autistic persons. Although not directly related to diagnosis, recognition of such gesture by a computer is a milestone nevertheless. Interestingly, the paper tests and compares the performance of Hidden Markov Model as well as Support Vector Machines. Autistic People tend to perform three classical actions: (i) Body Rocking; (ii) Hand Flapping; and (iii) Top Spinning possibly due to self defense or self stimulation [5]. The recognition of this behaviour is of immense importance as it could be used for classification and categorization of ASD level. Input data for the model was collected using orientation sequences of joints captured from RGB-D camera. Joint orientation data was OpenNI/NITE package was used on the extracted frame and four different machine learning model configurations - Diagonal–HMM, Spherical–HMM, Radial–SVM, and Polynomial–SVM were trained [5]. Correctly Classified Instances (CCI) was used as a metric to gauge performance. HMM in general provided higher accuracy in recognition across all three gestures with an average performance of 98.89% CCI as compared to SVM with an average performance of 94.52% CCI [5].

In addition to distinctive body gestures, People with ASD often exhibit fluctuations in their visual attention and gaze patterns. In a study of 32 infants and their parents, researchers used a variable Markov model (VMM) to create classification models for ASD and non-ASD subjects [6]. The VMM achieved an accuracy of 93.75% in identifying subjects with ASD [6]. Unlike hidden Markov models (HMMs), which are used to model systems with hidden states, VMMs can predict the probability of an event occurring based on known states and observable variables. This research is valuable because early diagnosis and intervention can help reduce ASD symptoms.

IV. Research Challenges

Every approach had limitations and issues pertaining to some part of the problem it overlooks or simplifies.

In the approach of estimating autism likelihood of children from ASD parents, there are factors for improvement. Only one level family ancestry and heritibility data is considered when modelling the HMM. Grandparents or grand-grandparents are not taken into account at all. Secondly, age is also another factor that has been neglected during this study even though it has a direct impact on the probability of conceiving children for both TD and ASD parents. For an initial model, the work presented is sufficient and satisfactory. However, with time and availability of newer and changing statistics the model would have to be updated.

While reviewing the second approach of looking at the dissimilarity in brain activity patterns, findings were congruous with the existing literature that indeed the ASD and TD people have different functional connectivity. This was one of the first attempt to classify brain activity into dynamic recurrent states. However, this study had two major constraints. One of the limitations of the study is the assumption of the HMM approach, which assumes that the state at a certain time point can be predicted without information of the time courses before that point. This leads to a short-range dependency between HMM states, which is inconsistent with previous research on the long-range dependency of brain states. As a result, the HMM may not be the best method for accurately characterizing brain states. Another limitation of the study is the choice of the number of HMM states, which is a free parameter and difficult to determine. Neither the sliding-window approach nor the HMM approach is capable of decomposing the explicit number of intrinsic states of brain activity. This makes it difficult to determine the correct number of states. Other than these two limitations, we encountered some difficulty on our end. The unfamiliarity with neuroscience terms was an obstacle to fully understand the depth of this study and we tried to bridge the learning gap at our best.

V. Conclusion

In this paper, we explored a holistic overview of three major approaches used in literature to study autism and make predictions regarding its diagnosis and severity. In the first approach, probability of autistic parents conceiving autistic children was computed using HMMs. The model was designed using the statistical data available. The second approach attempted to understand the similarities and dissimilarities between brain activity and underlying networks from fMRI data using HMMs. The third approach ventured on diagnosing autism using NAO robots by analyzing gaze and other typical behaviour of ASD children. Limitations regarding each approach were discussed. Work is still ongoing in this field and the future seems promising. All the approaches had a different purpose which contributed greatly to the world of autism. More efficient work is needed in order to optimize or solve other issues related to diagnosis and treatment of autism to make it convenient and cost efficient for everyone. We will most likely see HMMs being used more effectively for ASD diagnosis.

VI. Acknowledgment

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