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Predictive Analytics & Validation for Technology Intervention Recommendation System for Autism: A Machine Learning Framework

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Abstarct: This research aims at development and validation of a Technology Intervention Recommendation System (TIRS) for individuals with Autism. Numerous machine learning (ML) techniques have been used for the development of this system like KNN, Decision Tree, Support Vector Machine (SVM), Naïve Base etc. It has been observed that SVM technique outperform out of other ML techniques. The accuracy of the developed TIRS is found to be 98%, with precision 0.95 and AUC 0.98. TIRS has also been validated with a sample size of 100 (N=100) as compared to clinicians' predictions. It has been seen that TIRS is predicting interventions with an accuracy of 98%. Moreover, the time taken by TIRS to predict the interventions in 5 seconds only as compared to 5 minutes taken by the clinician.

Keywords: *Autism, ASD, Recommendation System, Intervention, TIRS, SVM*

I. Introduction

Autism spectrum disorders include social communication issues and repetitive behavior patterns, among other strengths and problems [1]. The most recent epidemiological studies indicate that 1 in 54 US children receive an autism diagnosis by the time they are 8 years old, reflecting the rise in the frequency of the condition in recent decades. Calls for increased surveillance have been raised in China and Europe, and similar trends have been seen in the UK, Australia, India, and the West Indies [1]. In Australia, the National Disability Insurance Scheme includes over 29% of people with autism, indicating a sizeable portion of the disability community [7].

Findings from studies [2] indicate that women in the West Indies are more likely to give birth to autistic children.

The ethnic makeup of the area has an impact on this chance. The Caribbean's inadequate resources make it difficult to address this health issue, despite this worrying development. The area lacks the resources and opportunities required for both adults and children with autism, making it difficult to address the problem through public education. Autism has a significant economic impact; in 2014, the USA invested an estimated $309,873,907 in autism research, the majority of which came from federal sources [8]. According to a study of the literature, the annual expenses of childhood autism in the UK and the US are £3.4 billion and $66 billion, respectively, with early intervention and other direct nonmedical costs accounting for a large portion of these costs [9]. When the impact on quality of life was taken into consideration, the estimated overall yearly expenses in Australia in 2010 were AUD$9.7 billion, or $87,000 per person annually [10]. There is no information available for the same in India or the West Indies.

Early intervention, which is a group of strategies intended to improve educational and developmental abilities for well-being and community involvement, is vital in helping people with autism [11]. There are many other types of intervention models that can be used, from professional therapy provided by speech, psychology, or occupational therapists to more all-encompassing methods such as the Applied Behavior Analysis or Early Start Denver Model [13, 14]. Each model has varying time and money expenditures, and the choice of intervention, its degree of intensity, and its adaptation to various circumstances varies. The main objective is to increase skill development for better well-being and community involvement in the short and long terms, despite the variety of early intervention programs. Finding the most successful therapies is still difficult, though. In their evaluation of the field's efficacy studies, Alonso and colleagues stressed the need for validated instruments to gauge more broadly defined functional outcomes including employment, social participation, and health-related quality of life [11].

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In addition to being beneficial for the individuals impacted, any technology that could help people with ASD who struggle with social skills would also save money. As a result of recent technical developments, clever, portable, and reasonably priced multimedia handheld devices like iPads and tablets are now available as assistive technology devices. These devices can offer low-cost technological treatments. Because these technology interventions may be easily tailored, require less time to construct, and are less expensive than hiring a therapist, they are particularly helpful in training children with ASD [6].

Studies have indicated that children diagnosed with Autism Spectrum Disorder (ASD) exhibit a greater preference for touch-sensitive technologies, including tablets and iPads, over manual methods like flashcards [8]. Compared to traditional approaches, tablets and iPads have several advantages since they are small, portable, and encouraging to kids. They can also eliminate the need for parents or other caregivers to assist with manual teaching [10]. Computers and tablets offer an educational way for kids with ASD to receive lessons and participate in group activities [11]. Tablets are systems that are repetitious, consistent, and predictable; they also require less social interaction and may be utilized at different speeds and levels of difficulty [12].

iPads and Android tablets have been regularly utilized to enhance social and communication skills [5–10]. When compared to the conventional picture card approach, the author [13] evaluated how effective iPads were as a communication tool and found that three of the five participants used iPads more frequently for requests. Furthermore, [14] used the iPads to provide children with autism with a video modeling therapy package intervention. The intervention, which involved prompts, reinforcement, and forward chaining, improved the participants' ability to write and understand numerical values. Author [16] examined whether a computer-based intervention improved child with ASD's ability to identify faces using a social skills rating scale.

Therefore, it may be concluded that, in the early stages following an autism diagnosis, applications in the form of technology interventions may be suggested. The current study focuses on creating and validating a technology intervention recommendation system (TIRS) that uses machine learning and is based on the impairments indicated by the autism diagnosis tool [9]. There isn't a validated system like that in literature. Thus, the null and alternate hypotheses for this investigation are as follows:

H0: The designed system accurately recommends the technology intervention based on the impairment.

H1: The designed system not accurately recommends the technology intervention based on the impairment.

II. Methodology

In the first phase, the child is diagnosed with the help of Autism diagnosis tool or with some traditional approaches like DSM-V, CARS etc. then the highly impaired area is detected [9]. In second phase, TIRS has been developed and used for interventions are recommended based on the highly impaired area as detected in phase 1. There were total twenty-four input symptoms and these input symptoms are further categorized into six major domains [9] for detection and recommendation of an intervention. Table 1 shows the Major Domains along with its symptoms and sample recommendation apps suggested by TIRS.

Table 1: Sample Apps recommended by TIRS

Major Domain	**Symptoms**	**Intervention Recommendation Apps/Android/iPad [27-28]**
Engagement in Society	1. Not making eye contact 2. Continues to be odd 3. Not preserving social ties 4. Incapacity to connect with others 5. Not maintaining eye contact	“LOOK AT ME, Stories2Learn, Social Detective, Findme-Autism, and Social Skill Builder”
Sentimental Reaction	1. Copying or emulating 2. Group Focus 3. Inappropriate emotional reaction 4. No Fear	"Just-In-Time In-Situ, Hands, Incorrect Planet, Life is Game"
Mental Reaction	1. Untrustworthy Attention 2. A pause in reaction 3. An uneven memory	“Can you Copy Me, Beyond Touch, Zarku, Empathico”

Communication	1. Said language is delayed 2. Nonverbal communication is difficult 3. Generates an odd voice 4. Repeating sounds	“My Drama, Autism Says, What's the Expression - All Ages, Teach Me”
Behavior Reaction	1. Habitual conduct 2. Issues with environment change 3. Abnormal conduct 4. Self-injury	" Educate Me, FaceMatch, MotorSkill, My Drama"
Sensual elements	1. Seldom responds to sensory input 2. Unaffected by discomfort 3. peculiar in terms of smell, touch, or perception 4. Maintain a prolonged gaze	"Gaze, Xensation, The Blueroom, Sensory Room"

Figure 1 shows the methodology used for the development of TIRS. It can be observed that various machine learning techniques have been implemented to develop TIRS and then compared to evaluate the more optimum technique for the development of TIRS.

Fig 1: Methodology for TIRS

It can be seen in the figure that initially after the detection of autism and highly impaired area, the data of various apps used as recommendation for that particular impaired area was collected from various health care centers or autism care centers. Then the data was structured and formatted for training and testing, 75% data has been used for training and 25% data has been used for testing. Finally, various Machine Learning approaches were implemented like SVM, Decision Tree, KNN etc. and the performance have been monitored. The results were compared with clinicians' recommendations and if the system is not performing up-to-the-mark more data will be given for training the model. It has been observed from the Figure 2 that corresponding to each symptom an app has been recommended. The designed system after evaluating the highly impaired area gives the recommendation.

Intervention Recommendation System			
Major Domain	**Symptom**	**Recommended App Intervention**	**App Link**
Social Participation	Not following eye gaze	LOOK AT Me	https://play.google.com/store/apps/details?id=com.lookatme.membership

Fig 2: Output Window of the Intervention Recommendation System based on Highly Impaired Symptom

It has been observed that, in the aforementioned instance, the system will suggest the app "LOOK AT Me" along with the link, since the extremely degraded major domain was identified as "Social Participation" and the symptom as "Eye Gaze Lack." The developed system is the first of its sort in the literature, as far as we know.

III.Results And Discussion

Various machine learning algorithms have been employed in this work to train the models. Every algorithm operates differently and has various performance metrics when applied to a dataset. Average results from the K-Nearest Neighbor (KNN) algorithm were 75% for accuracy, 80% for precision, 70% for recall, 75% for F-score, and 75% for AUC. The SVM model has 98%, 95%, 96%, 97%, and 98% for accuracy, precision, recall, F-score, and AUC, respectively. The Naïve Bayes Classifier overfits the data, yielding 100% accuracy, precision, recall, f-score, and AUC. Ten K-fold cross validation has been employed to solve this issue, but the outcomes stayed the same. The DTC's accuracy, F-score, and AUC are 96%. The ratings for recall and precision are 93% and 94%, respectively. The accuracy and F-score of the Random Forest on the trained and test datasets are 92%. Recall is at 85%, AUC is at 92%, and accuracy is at 84%.

While every classifier demonstrated good performance on the provided dataset, the Support Vector Machine and Decision Tree models demonstrated superior performance with comparable outputs, while the K-Nearest Neighbour model shown mediocre performance on data with lower scores in comparison to the other four models. The predictive analysis of several machine learning methods is displayed in Table 2.

Table 2: Predictive analysis of various machine learning algorithms

	SVM	**DTC**	**RFC**	**KNN**	**Naive**
Accuracy	0.98	0.96	0.92	0.75	1.0
Precision	0.95	0.94	0.84	0.80	1.0
Recall	0.96	0.93	0.85	0.70	1.0
F-Score	0.98	0.96	0.92	0.75	1.0
AUC	0.98	0.96	0.92	0.75	1.0

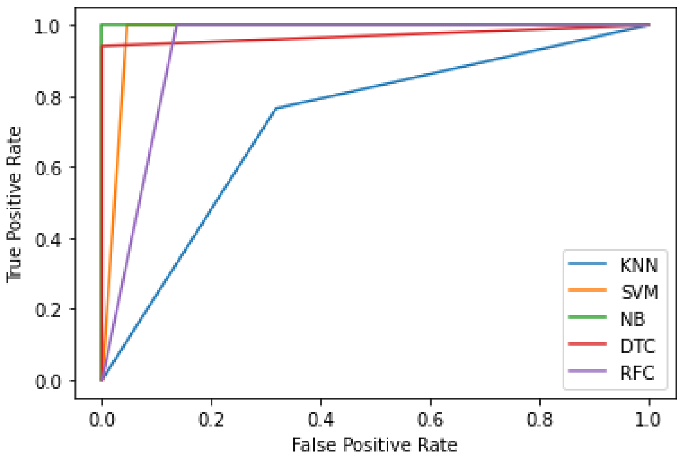

Fig 3: True Positive rate versus False Positive Rate for various ML techniques

Figure 3 shows the classification of true positive rate and false positive rate for various machine learning algorithms. It has been clearly visible that SVM is outperforming as compared to all other ML techniques.

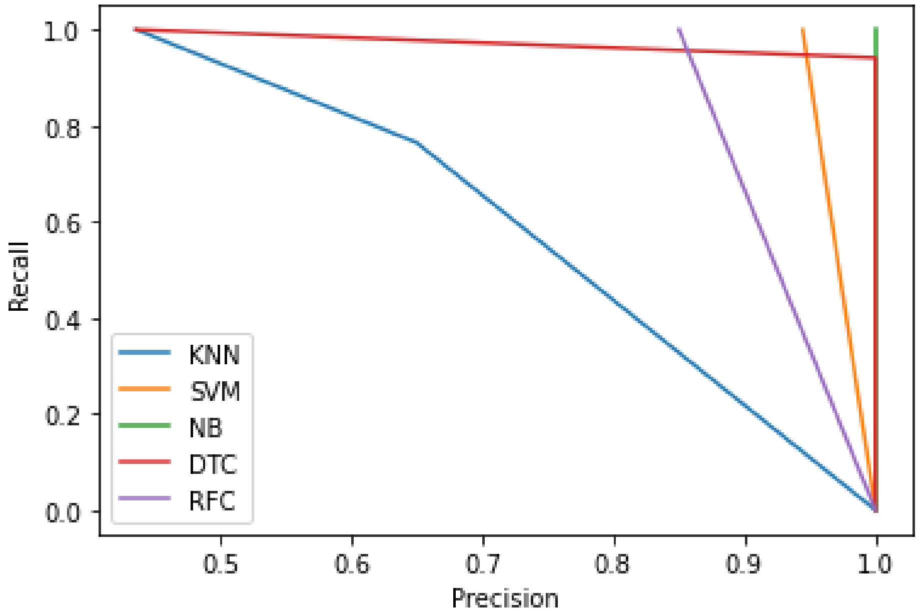

Fig 4: Recall versus Precision for various ML techniques

Figure 4 shows recall versus precision for various ML techniques and again it has been seen that SVM is performing best out of various ML techniques.

IV. Validation

i) Methods and materials

a) Participants

Prior to beginning this work, signed informed consent was obtained from each parent and caregiver. Participants were chosen from a number of Jalandhar, Punjab, India, special schools. A meeting with all parents/caretakers and the kid was scheduled prior to the start of the work in order to outline the actions of the study and emphasize the importance of consistent attendance. This study involved 100 participants in the autism group, aged 3 to 5 years (mean age 4.2 years; 70 males and 30 females). All ASD children were diagnosed to have autism by meeting Diagnostic and Statistical Manual of Mental Disorders, 4th Edition (DSM-IV) criteria. Moreover, all the children with autism met autism diagnostic interview-revised (ADI-R) criteria for ASD. All the participants were dextral and had normal or corrected to normal vision. None of the children received any psychoactive medication during the study.

When a youngster met the Diagnostic and Statistical Manual of Mental Disorders, Fourth Edition (DSM-IV) criteria, a diagnosis of autism was made. Additionally, every autistic child fulfilled the revised autism diagnostic interview (ADI-R) criteria for ASD. Every subject had normal or corrected to normal eyesight and was dextral. Throughout the trial, no psychoactive medicine was given to any of the youngsters.

ii) Tools Used

To validate this developed tool, clinicians' recommendations were compared with the predicted results of the tool.

iii) Data Collection

The data was gathered by the experts and fed to the developed system. All parents/caretakers were given full information about the procedure and the methodology used. The data has been cleaned before the use and missing values have been replaced with the average value. The data was normalized as verified from SPSS.

iv) Data Analysis and Validation

Data analysis was performed using "SPSS" technique to standardize the developed system. In the experiment, Chi Square test was used to predict the true positive cases versus the true negative cases. It has also been analyzed from the ANOVA that there is no significant difference between both the TIRS predictions and clinicians' predictions ($p>0.001$). It has been observed from Figure 5 that TIRS is clearly able to predict the interventions as similar to clinicians' recommendations with an accuracy of 98 % (N=100). The specificity of TIRS was found to be 98.2 and 98.2 was the observed sensitivity.

			Developed_Tool_Prediction True Prediction	Total
Actual_Recommendation	False Prediction	Count	2	2
		% within Actual_Recommendation	100.0%	100.0%
		% within Developed_Tool_Prediction	2.0%	2.0%
		% of Total	2.0%	2.0%
	True Prediction	Count	98	98
		% within Actual_Recommendation	100.0%	100.0%
		% within Developed_Tool_Prediction	98.0%	98.0%
		% of Total	98.0%	98.0%

Figure 5: Actual Recommendations by Clinician versus Predicted Recommendations by TIRS

Hence, it can be said that the formulated null hypothesis (H0) "The designed system accurately recommends the technology intervention based on the impairment" can be accepted and alternate hypothesis (H1) can be rejected.

i) Time Taken

The time taken by TIRS to execute the recommendation when input symptom is applied is 5 seconds in comparison to 5-10 minutes time taken by the clinician.

V. Conclusion And Future Scope

The designed technology intervention recommendation system (TIRS) accurately determines the interventions as similar to the clinician's recommendations. In addition, TIRS recommends interventions in very less time as compared to the clinician. The large dataset with more interventions and therapy center locations will make this developed system more accurate and efficient. Hence, it can be said that this system can be used by clinicians, parents, care-takers/givers etc. for the intervention recommendations at an early stage so that time can be saved and skills can be developed at an early age. It will help the clinicians', parents and hence the society to ease the lives of individuals with autism

Statements

Conflict of Interest

The authors attest that there are no known conflicts of interest related to this publication, nor has there been any substantial funding for this research that would have affected the findings.

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