MPredA: A Machine Learning Based Prediction System to Evaluate the Autism Level Improvement

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Abstract. This paper describes the developmental process of a machine learning-based prediction system to evaluate autism Improvement level (MPredA), where the concerned user (parents or clinical professionals) can evaluate their children's development through the web application. We have deployed our previous work (mCARE) data from Bangladesh for prediction models. This system can predict four major milestone parameter improvement levels of children with ASD. In this four-broad category, we have classified into four sub-milestones parameters for each of them to predict the detailed improvement level for each child with ASD. This MPredA can predict 16 milestone parameters for every child with ASD. We deployed four machine learning algorithms (Decision Tree, Logistic Regression, K-Nearest Neighbor, and Artificial Neural Network) for each parameter with 1876 data of the children with ASD to develop 64 prediction models. Among the 64 models, we selected the most accurate 16 models (based on the model's accuracy and evaluation scores) to convert pickles file for the MPredA web-based application. For the prediction system, we have determined the most ten important demographic information of the children with ASD. Among the four-machine learning algorithms, the decision tree showed the most significant result to build the MPredA web-based application. We also test our MPredA -web application by white box testing and get 97.5% of accuracy with real data.

Keywords: Autism Spectrum Disorder (ASD) · Milestone Parameter (MP) · Prediction of MP Improvement · Demography of children with ASD · Importance of demography

H. Lewy and R. Barkan (Eds.): PH 2021, LNICST 431, pp. 416–432, 2022.
https://doi.org/10.1007/978-3-030-99194-4_26

Aberration

Autism Spectrum Disorder (ASD): Behavioral development disability among the children at an early age

Milestone Parameter (MP): The list of early age children's behavioral achievement

1 Introduction

In 1943, Kanner first identified the disorder in the children's behavior [1], and later this neurodevelopmental disorder [2] is known as Autism Spectrum Disorder (ASD). Now, this ASD is a global problem [3], and people of all societal levels suffer from ASD [4]. About 1%–1.5% of children have been suffering from ASD in developed countries [5]; for example, in the United States, 1 out of 54 children have ASD symptoms [6, 7]. Though in developed countries, we have a statistic of the ASD number, in developing countries, especially in low-and-middle-income countries, this scenario is not as good as than developed countries. In developing countries, sometimes they do not properly understand the ASD, and there ASD number is largely unknown. [8] So, children with ASD do not get the proper and early treatment in those countries. In the globe, about 46% of children with ASD do not get the proper diagnosis after identifying the ASD symptoms. [8] Sometimes, parents think this is their curse from GOD. [9, 10] They blame themselves for their previous sin and having a child with ASD. This superstitious belief of the people makes this disorder more complex for children with ASD. [11] But proper ASD knowledge of parents, early identification of ASD [12], and starting of the treatment process, [13] developing attitude towards the children [14] help to develop the children with ASD. And it is scientifically proved that the society's positive point of view towards the family with ASD children and demography of the children with ASD have a significant impact on the children's (with ASD) development.[15, 16] In this study, based on this concept (demography's impaction on children with ASD development), we have developed a machine-learning-based web application that can predict the milestone parameter (four major types) depending on children's demography (ten demographical data).

Currently, most of the innovative work (by deploying technology) and tools are for early identification, recognition of ASD [12, 17, 18], or diagnosis in different phases of the treatment process [2]. There is no such tool that can predict the improvement level (milestone parameter) based on the children's demography. This tool will be helpful for both the clinical professional and the parents or primary caregiver to know earlier the children's developmental or improvement level based on their demography. However, there has a little research-based work on proving the demographical importance on the children (with ASD) [2]. This will be the first research-based (by machine learning models with real data set) web tool, where both caregiver or care-practitioner can give their children's baseline data and the demographic information to get the real-time predicted improvement level of their children based on their provided data.

The main novelty of this work is that parents can update or develop their demography if they learn earlier the improvement level of their children (with ASD) based on their current demography or which demography is the most important for their children's (with ASD) development. In this study, we broadly classify and predict the 16 different milestones parameters level into four major categories of (i) daily living skills, (ii) communication, (iii) motor skills, and (iv) socialization. Based on our previous work (mCARE) [19] data, we have selected the most ten important demographical data types to build robust machine learning models. Then we used these models to develop the web-based MPredA. Therefore, MPredA can predict the milestone parameter improvement level of children with ASD with minimal error. Since currently, we rarely have an accurate system or state-of-the-art system that can predict this improvement level; for this reason, we have a plan to deploy this system in our future project to observe the MPredA's scientific contribution.

The rest of the paper is organized as follows. Section 2 summarizes some related works. Section 3 describes the methodology of MPredA for predicting the milestone parameters. Section 4 illustrates the experimental studies. Finally, Sect. 5 concludes the paper.

2 Related Works

Recently some research-based work has been developed to inform the demographical importance of developing children with ASD. The approach proposed in [20] is machine learning-based research work, where a set of demographical-based machine learning models developed to predict the children's (with ASD) development. In this work, four machine learning algorithms have been deployed to build the models to predict the children's (with ASD) "Daily Living Skills" improvement level. They recommend ten important demographical data, which are very significant to the children's development. Based on the findings in this study, we have extended the data set for four major milestone parameters with 1876 data and built 64 machine learning models. Among these models, we selected the best 16 models to develop our web-based MPredA system.

Another machine learning-basedwork has been developed by Tarik et al.[2] to measure the developmental delays of children with ASD by deploying the home videos in Bangladesh. They used a 2-classification layer of Neural Network with 85% of accuracy to predict the "risk scores" for the children with ASD. This prediction-based work is also helpful for the early detection of autism remotely. Though this work used the Bangladeshi data, the authors' used the US data to train the model. This makes the model culturally divergent. Maenner et al. [21] evaluated the ADDM status of children with ASD based on the machine learning model by deploying the word and phrases during the children's developmental evaluation period.

3 Machine Learning Based Prediction System for Autism Level Improvement (MPredA)

MPredA has been proposed and developed a web-based application [22] that can easily predict the developmental level based on the children's demographic information. It consists of several steps, which are described as follows. Figure 1 is the flow chart of the steps of MPredA.

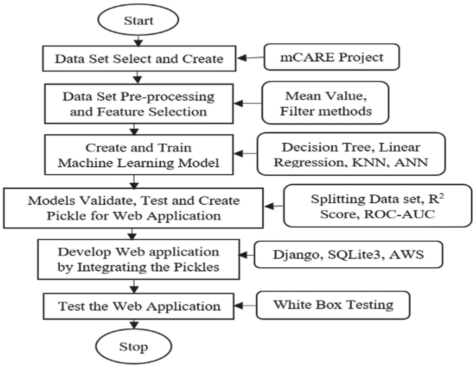


Fig. 1. Outline of research design.

3.1 Select and Create Data Set

This study has deployed the mCARE (Mobile-based Care for children with Autism Spectrum Disorder using Remote Experience Sampling Method) project [19] data. We had approval from the Marquette University Institutional Review Broader (Protocol number HR-1803022959) for deploying the data which had been collected from four centers in Bangladesh. In this study, we have used the "test group" patients' data, who had been monitored and intervened by the clinical coordinators for one year. These data had been collected by the mCARE system [23], and the patient distribution among the four centers for the test group has been shown in Table 1.

Table 1. Test group patient distribution among the four centers.

Serial	Center name	Patient distribution
		Test group (n = 150)
1	The National Institute of Mental Health (NIMH) [24]	50
2	The Institute of Pediatric Neuro-disorder & Autism (IPNA) [25]	50
3	Autism Welfare Foundation (AWF) [26]	25
4	Nishpap autism foundation [27]	25

Since MPredA's machine learning models have been developed based on the children's demography, Table 2 shows the participants' demography in the mCARE project.

From Table 2, we can observe that in mCARE, there had a total of 45 demographic information in 10 broader categories. From this 45 demography, in this study, we have selected ten important demography (details selection process in step 2) for building the machine learning-based training models. Besides the demographic information, we need the specific milestone parameters' baseline level (at the study's starting point) and improvement level (at the ending point) by the corresponding demographic information.

Table 2. Test group participants (n = 150) demographic information.

Serial	Demographics	Participant, n (%)	Serial	Demographics	Participant, n (%)
1	Patients' age: 2–6 6–9	37 (24.7%) 113 (75%)	6	Father's occupation: Service Business Cultivation Other Unemployed	70 (46.7%) 45 (30.0%) 1 (0.7%) 7 (4.7%) 23 (15.3%)
2	Gender: Male Female	124 (82.7%) 26 (17.3%)	7	Mother's occupation: Student Unemployed Housewife Service Business Cultivation Maid Other Not applied	0.0 (0.0%) 0.0 (0.0%) 124 (82.7%) 17 (11.3%) 4 (2.7%) 0 (0.0%) 1 (0.7%) 1 (0.7%) 3 (2.0%)
3	Educational opportunity for the patients: Never went to school Went to usual academic school but failed to continue study Went to specialized school but failed to continue study Currently he/she is going to usual academic school Currently he/she is going to specialized academic school	34 (22.7%) 22 (14.7%) 4 (2.7%) 12 (8.0%) 78 (52.0%)	8	Family expenditure per month (in thousand taka)[a]: <15 K 15–30 K 30–50 K >50 K	19 (12.7%) 44 (29.3%) 31 (20.7%) 56 (37.3%)
4	Father's educational Level: Primary Secondary Undergraduate Graduate Postgraduate	29 (19.3%) 23 (15.3%) 23 (15.3%) 29 (19.3%) 46 (30.7%)	9	Family size: Nuclear Extended	113 (75.3%) 37 (24.7%)

(*continued*)

Table 2. (*continued*)

Serial	Demographics	Participant, n (%)	Serial	Demographics	Participant, n (%)
5	Mother's educational Level: Primary Secondary Undergraduate Graduate Postgraduate Student	19 (12.7%) 37 (24.7%) 25 (16.7%) 32 (21.3%) 37 (24.7%) 0.0 (0.0%)	10	Living area: Urban Semiurban Rural Slum	120 (80.0%) 15 (10.0%) 15 (10.0%) 0.0 (0.0%)

a. US $1 = 84.70 Taka (as of June 22, 2021).

For that reason, we have developed a total of 16 data sets (based on the milestone parameters) in four main categories of (i) Daily Living Skill, (ii) Communications, (iii) Motor Skills, and (iv) Socialization. For these 16 data sets, in MPredA, we have built 64 machine learning training models (four machine learning models for each data set). We have deployed our 150 test group participants to build these data set, and in total, we got in total 1875 instances (data) for the 16 data set. Table 3 shows the 16 data sets (Four types of Milestone Parameters) with the data set size, n (participants number for building each data set).

3.2 Data Set Preprocessing and Feature Selection

After creating the 16 data sets, in this step, we preprocessed the data set by the following steps:

Data Cleaning: We have observed some noisy data (filled by negative value) in our dataset, which had no impact on the machine learning models. We removed these noisy data. After that, we found some missing, especially the age and family expenditure columns. We deployed the most popular method, "the attribute mean value" [28, 29], to handle these missing values.

Feature Extraction and Binarization: This is a very critical step in building our data sets to deploy in machine learning algorithms. Initially, our data set had some non-numeric columns (13 out of 19 columns) with more than one feature in one column (for example, in father education, there had all educational level's information of the mothers in one column). In this step, we did the feature extraction and binarization process simultaneously and covert data set on 45 (according to the Table 2 demographic information) columns with an only numerical value ('0' for negative and '1' for positive value). Besides these, we also applied the MinMaxScaler [30] to convert all the features in the range of 0 to 1; this conversion is very important to increase the machine learning algorithms' performance [31, 32].

Feature Selection: After getting the extraction features (total 45) from the previous step, we deployed the "Filter Method" [33, 34] to select the most important features

Table 3. MPredA data sets with participants number for building the predictive training models.

Serial	Milestone type and parameter	Number of patient (n)	Serial	Milestone type and parameter	Number of patient (n)
Daily living skills			Motor skills		
1	Asks to use toilet	105	9	Draws circle freehand while looking at example	136
2	Brushes teeth	140	10	Glues or pastes 2 or more pieces together	130
3	Buttons large buttons in front, in correct buttonholes	109	11	Jumps with both feet off floor	104
4	Urinates in toilet or potty	112	12	Runs smoothly without falling	119
Communication			Socialization		
5	Listens to a story for at least 15 min	100	13	Answers when familiar adults make small talk (eg. If asked 'how are you_' says 'fine')	120
6	Modulates tone of voice, volume, and rhythm appropriately (eg. Does not consistently speak too loudly, too softly or in a monotone)	100	14	Keeps comfortable distance between self and others in social situations	134
7	Points to at least 5 body parts when asked	116	15	Talks with others about shared interests (eg. Sports, tv shows, cartoons)	126
8	Says month and day of birthday when asked	116	16	Use words to express emotions (eg. 'I am happy', 'I am scared')	109

(*continued*)

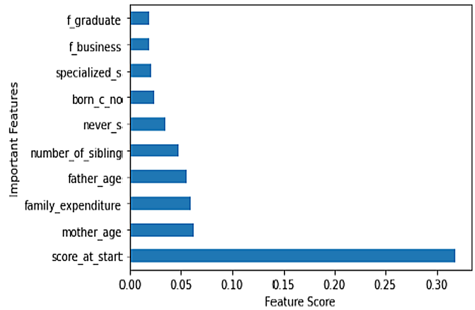
Table 3. (*continued*)

Serial	Milestone type and parameter	Number of patient (n)	Serial	Milestone type and parameter	Number of patient (n)
Total		1876			

from our extracted data sets. We have deployed four popular feature selection approaches (univariate selection [35], feature important [35], correlation matrix with heatmap [36], and information gain [37]) under the filter method. We selected the most ten important features from the 45 features of our data sets based on the results of these four feature selection approaches. Figure 2 shows the results of the most important features from univariate selection [35], feature important [35] approaches.

	Specs	Score
3	family_expenditure	2.094082e+06
45	score_at_start	2.284679e+02
27	never_s	2.897760e+01
28	specialized_s	1.257800e+01
1	father_age	9.745763e+00
8	m_undergraduate	9.046455e+00
6	m_graduate	8.050115e+00
30	usual_s	6.412382e+00
40	born_c_yes	4.149451e+00
34	rural	2.607987e+00

(a)



(b)

Fig. 2. Most ten important features of the data set are based on (a) Univariate selection and (b) Feature important approaches.

We combine the result from the four feature selection methods and select the following features: (i) baseline data, (ii) family expenditure, (iii) father age, (iv) mother age, (v) father occupation as a businessman, (vi) mother as a housewife, (vii) children's education in a specialized school, (viii) mother's education level (undergraduate), (ix) living in urban, and (x) number of siblings. We also have valid these selected features by analyzing our data.

Data Set Quality Assurance: According to [38], the lower R-value (co-officiant value between two columns) indicates the higher classification accuracy. We randomly selected two columns from our data set (whole data set with 1876 instants) and got R = 0.01 which very much lower value (close to zero) that indicates an excellent data set quality according to the categorical overlap evaluation method [38].

3.3 Build Machine Learning Models

For developing the web-based prediction application for predicting the milestone parameter of the children with ASD, we have deployed four supervised classification algorithms

(Decision Tree (DT) [39], Logistic Regression (LR) [40], K-Nearest Neighbor (KNN) [41], and Artificial Neural Network (ANN) [42]) to build the machine learning-based prediction models. In this step, we developed 64 machine learning models for a total of 16 milestone parameters. We validated the models by determining the models' accuracy with the train-test split method [43], where we have used 80% data for the training data set and 20% for the testing data set. Then we evaluated the models by two methods: (i) R^2 value [44] and (ii) ROC-AUC value [45]. The summary of all models' accuracy with evaluation score has been shown in Table 4.

Table 4 shows all models' accuracy with the evaluation scores. Here every row represents every milestone parameter, and we show the four separate machine learning models' results in the same row. The accuracy of each model has been shown by percentage, and the evaluation scores (by r2 scores and ROC-AUC value) are also mentioned with the accuracy.

3.4 Analyze the Models and Create Pickles

From the 64 prediction models, we have selected the best 16 models for 16 milestone parameters based on the models' accuracy and evaluation scores (Bold in Table 4). Based on the accuracy and performance of the models, we have selected the best models for each milestone parameter and created 16 pickles file [46]. These pickle files have been deployed to build the web-based Prediction System to Evaluate the Autism Level Improvement (MPredA).

3.5 Create and Test the Web Application

We have used the best 16 pickle files for developing the web application to predict the milestone parameter improvement level based on the children's (with Autism) demography. These pickles have been run on the Amazon web Service (AWS) [47] server to predict the 16 milestones parameters. The website front-end was designed and implemented by Django [48]. We have used the SQLite3 database [49] to store the data in this web application. The web application of MPredA is available on the web named as "MPredA" [22]. After developing the web application, we have tested the web application by "White Box" [50] testing. Our expert user and phycologist test the web application in this testing phase. For the 16-milestone parameters, initially, we randomly selected 80 input sets (5 for each parameter) and separated them for testing purposes. We observed our web application has 78 correct results from 80 sets of inputs in the testing phase, which is 97.5% accuracy.

4 Experimental Analysis

4.1 Experimental Setup

MPredA has been developed under the environment on Apple M1 chip with 8-core CPU, 8-core GPU, and 16-core Neural Engine with 8.0 GBytes of RAM running on Big Sur operating system. For developing the machine learning models, we have deployed four

Table 4. Summary of the accuracy with evaluation scores of all prediction models based on the demography for four milestone parameters.

	Parameter types	DT	LR	KNN	ANN
Daily living Skills Daily living Skills aily Living Skill	Asks to use toilet	86% $R^2 = 0.21$ roc_auc = 0.77	90% $R^2 = -.11$ roc_auc = 0.68	**90%** $\mathbf{R^2 = 0.53}$ **roc_auc = 0.84**	84% $R^2 = -.09$ roc_auc = 0.622
	Brushes teeth	**96%** $\mathbf{R^2 = 0.46}$ **roc_auc = 0.75**	96% $R^2 = -.04$ roc_auc = 0.51	96% $R^2 = -.04$ roc_auc = 0.91	93% $R^2 = 0.09$ roc_auc = 0.81
	Buttons large buttons in front, in correct buttonholes	**91%** $\mathbf{R^2 = 0.54}$ **roc_auc = 0.83**	91% $R^2 =-.10$ roc_auc = 0.77	82% $R^2 = 0.27$ roc_auc = 0.83	82% $R^2 = -.53$ roc_auc = 0.9
	Urinates in toilet or potty	96% $R^2 = 0.62$ roc_auc = 0.98	**1.0%** $\mathbf{R^2 = 1.0}$ **roc_auc = 1.0**	91% $R^2 = -.10$ roc_auc = 0.51	86% $R^2 = 0.03$ roc_auc = 0.60
Communication	Listens to a story for at least 15 min	**85%** $\mathbf{R^2 = 0.39}$ **roc_auc = 0.86**	80% $R^2 = 0.19$ roc_auc = 0.35	76% $R^2 = 0.03$ roc_auc = 0.77	80% $R^2 = 0.13$ roc_auc = 0.74
	Modulates tone of voice, volume, and rhythm appropriately (eg. Does not consistently speak too loudly, too softly or in a monotone)	**95%** $\mathbf{R^2 = 0.78}$ **roc_auc = 0.93**	80% $R^2 = 0.17$ roc_auc = 0.88	90% $R^2 = 0.58$ roc_auc = 0.90	55% $R^2 = 0.11$ roc_auc = 0.67
	Points to at least 5 body parts when asked	83% $R^2 = 0.33$ roc_auc = 0.83	79% $R^2 = 0.06$ roc_auc = 0.78	**92%** $\mathbf{R^2 = 0.67}$ **roc_auc = 0.94**	63% $R^2 = 0.05$ roc_auc = 0.66
	Says month and day of birthday when asked	**92%** $\mathbf{R^2 = 0.66}$ **roc_auc = 0.91**	92% $R^2 = -.09$ roc_auc = 0.73	92% $R^2 = 0.40$ roc_auc = 1.0	71% $R^2 = 0.13$ roc_auc = 0.68

(*continued*)

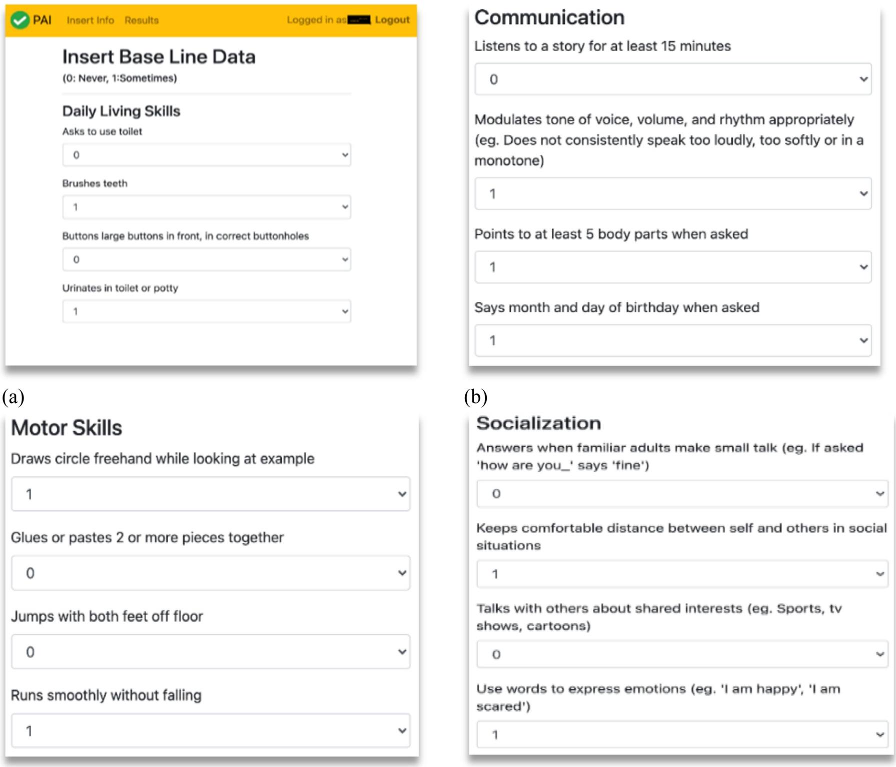
Table 4. (*continued*)

	Parameter types	DT	LR	KNN	ANN
Motor Skills	Draws circle freehand while looking at example	85% $R^2 = 0.38$ roc_auc = 0.8	**93%** $\mathbf{R^2 = 0.58}$ **roc_auc = 0.91**	71% $R^2 = -.52$ roc_auc = 0.70	93% $R^2 = -.25$ roc_auc = 0.87
	Glues or pastes 2 or more pieces together	92% $R^2 = 0.57$ roc_auc = 0.95	**96%** $\mathbf{R^2 = 0.46}$ **roc_auc = 0.98**	85% $R^2 = 0.38$ roc_auc = 0.83	81% $R^2 = 0.21$ roc_auc = 0.78
	Jumps with both feet off floor	**1.0%** $\mathbf{R^2 = 1.0}$ **roc_auc = 1.0**	90% $R^2 = 0.22$ roc_auc = 0.65	91% $R^2 = 0.39$ roc_auc = 0.67	81% $R^2 = 0.10$ roc_auc = 0.81
	Runs smoothly without falling	**98%** $\mathbf{R^2 = 0.48}$ **roc_auc = 0.75**	96% $R^2 = -.04$ roc_auc = 0.26	95% $R^2 = -.04$ roc_auc = 0.41	92% $R^2 = -.11$ roc_auc = 0.32
Socialization	Answers when familiar adults make small talk (eg. If asked 'how are you_' says 'fine')	**92%** $\mathbf{R^2 = 0.62}$ **roc_auc = 0.94**	79% $R^2 = 0.06$ roc_auc = 0.72	75% $R^2 = -.03$ roc_auc = 0.70	67% $R^2 = 0.10$ roc_auc = 0.57
	Keeps comfortable distance between self and others in social situations	**93%** $\mathbf{R^2 = 0.71}$ **roc_auc = 0.92**	81% $R^2 = -.23$ roc_auc = 0.65	81% $R^2 = 0.04$ roc_auc = 0.78	81% $R^2 = 0.04$ roc_auc = 0.63
	Talks with others about shared interests (eg. Sports, tv shows, cartoons)	88% $R^2 = 0.51$ roc_auc = 0.89	92% $R^2 = 0.64$ roc_auc = 0.86	**1.0%** $\mathbf{R^2 = 1.0}$ **roc_auc = 1.0**	73% $R^2 = 0.20$ roc_auc = 0.79
	Use words to express emotions (eg. 'I am happy', 'I am scared')	91% $R^2 = 0.54$ roc_auc = 0.83	**1.0%** $\mathbf{R^2 = 1.0}$ **roc_auc = 1.0**	68% $R^2 = -0.32$ roc_auc = 0.61	86% $R^2 = 0.34$ roc_auc = 0.76

supervised classifiers ((i) tree.DecisionTreeClassifier [51], (ii) LogisticRegression class [52], (iii) KneighborsClassifier [53], and (iv) keras.Sequential [54]) from the sklearn library [55] of Python [56]. We have used the 6.2.0 Jupyter Notebook [57] in 4.10.1 Anaconda Navigator [58]. For developing the web application, we have deployed Django 3.2.4 [48] framework with Amazon Web Service (AWS) [47]. The web application of MPredA is available on the web named as "MPredA" [22].

4.2 Experimental Result

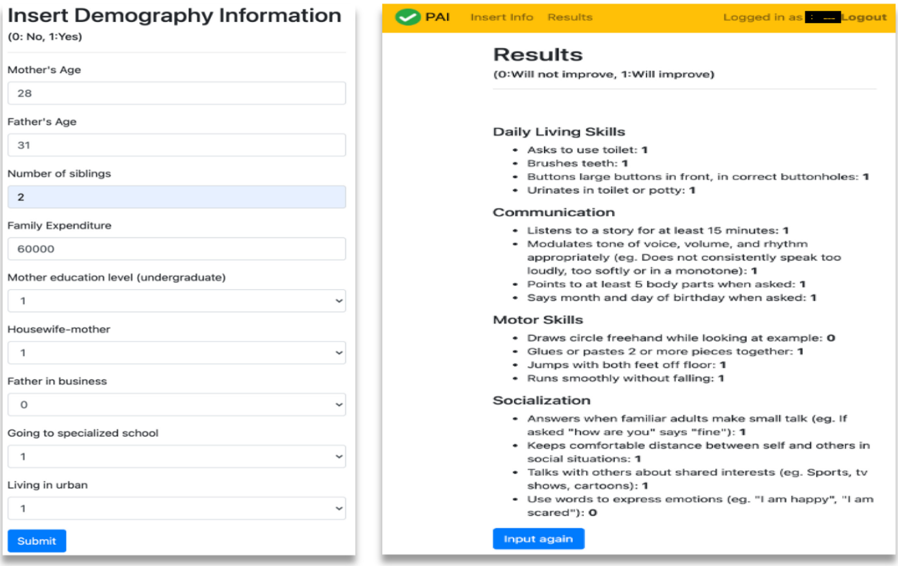
For predicting the milestone parameters, the caregiver or care-practitioner has to give two types of information the MPredA web application [22]. The first type of input is the baseline data of the children (with ASD) in 16 milestone parameter fields (in four major categories). Figure 3 shows the screenshot of an anonymous children's (with ASD from mCARE dataset) baseline data for four major milestone parameter categories.



(c) (d)

Fig. 3. A screenshot from MPredA web application to input the children's baseline data: (a) Daily living skills, (b) Communication, (c) Motor skills, and (d) Socialization.

After proving the baseline data, the caregiver or care-practitioners must input the selected (ten) demographical information into the system. Figure 4(a) shows the demographical input form of the MPredA web application. Then MPredA web application parses these data to the pickles at the AWS server and shows the children's predicted milestone improvement level data by the result page. Figure 4(b) shows the result page of MPredA web application based on the data provided by Fig. 3 and Fig. 4(a) children's data.



(a) (b)

Fig. 4. A screenshot from MPredA web application (a) input page for the children's demographic information, (b) result page from MPredA web application.

4.3 Discussions

The experiment result presented in the above section shows how MPredA can predict the improvement level of milestone parameters of children with ASD. This mHealth research-based web application can be used by both the primary caregiver and also the care practitioner. They can use this application at the starting of the treatment process to know the development level (milestone parameter) based on the children's demography. And this web application can be used both in the home and in the clinical setting to determine the children's milestone parameter improvement level. However, the user of this application can determine all 16 milestone parameters' improvement level at a time by giving all baseline data (showed as previous experience result), or they can determine only one milestone parameter in one run by giving only the baseline data that they want to determine the improvement level and leaving the other baseline data blank. Since we determine the improvement level of the milestone parameters by running separate pickle files with a separate machine learning model, it will not have any impact if any user leaves blank on the baseline data or wants to determine only one milestone improvement level in one run of the application. The main advantage of this application is determining the improvement level of a children's (with ASD) milestone parameter without any clinical intervention. It can be done at the starting point of the treatment process. And parents can know their children's improvement level based on their demography as early; they can update or change their demography to develop their children's milestone parameters. In this study, we have worked on 16 milestone parameters in four major categories, which are very common in children with ASD. This data set size is another challenging issue in our work, as the real data in this area is very rare to collect. But in this study, we have tried to give more focus on the data integrity and quality to get the more accurate result to determine the milestone parameter improvement level.

5 Conclusion

In case to predict the milestone parameter improvement level, MPredA will be the first web application based on the children's (with ASD) demography. We have used four robust machine learning algorithms with real patient data to build the prediction models in this system. The model used for developing MPredA-web applications is the most accurate and competitive (selected 16 models among the 64 models). Among the four machine learning classifiers, we have observed a decision tree as an effective and accurate classifier for this kind of data. As we have an excellent accuracy of all models and the web application (97.5% accuracy with white box testing), this machine learning-based application will be a mental health development tool for children with ASD. For the web application, the caregiver can learn the importance of their demography for their children's development, and they can update or develop their demography based on their children's development; whereas the care-practitioners can know the improvement level of children before starting the treatment process and they can take the proper treatment or therapy based on the prediction result. Though this type of real data set is very rare, we have the challenge of building the machine learning models with this limited data set. It is expected that we will deploy this system with the same data set to build a recommendation system for the development of children with ASD.

Acknowledgement. This study has been partially supported by an NIH grant (1R21MH116726–01). The authors are thankful to 4 specialist autism health care centers and institutions in Bangladesh: The Institute of Pediatric Neuro-disorder & Autism (IPNA) Bangladesh, The National Institute of Mental Health (NIMH), Autism Welfare Foundation (AWF), and Nishpap Autism Foundation and their respective departments for their continuous support throughout this study.

Conflicts of Interest. None declared.

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