Patients with SMID Signature Detection by Multimodal Sensing Data Analysis

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ABSTRACT

Patients with severe motor and intellectual disabilities (SMID) have difficulty communicating, placing a heavy burden on their families. In order to solve this problem, the authors are working on the development of a system that can notify the "unusual" state of severely ill children. In this study, daily life scenes of severely ill children were observed at fixed points, and multiple regression analysis was performed using the data before and after sputum expectoration of four severely ill children. As a result, three common Action Unit (AU) items extracted from four patients were placed in the input layer, and the analysis was performed using a 3-layer neural network. We tried two methods of the hidden layer activation function: the sigmoid function and the hyperbolic tangent function. The activation function of the output layer was the sigmoid function. Consequently, when the number of units in the first layer of the hidden layer is three, the number of units in the second layer of the hidden layer is two, and the activation function of the hidden layer is a hyperbolic tangent function, the most accurate classification was achieved.

Keywords: Patients with SMID (Severe Motor and Intellectual Disabilities), Action Unit, Neural network, Hyperbolic tangent function , Sigmoid function , Multimodal

Ⅰ. Introduction

Advances in medical technology have improved the survival rate of patients with severe motor and intellectual disabilities (SMID), who require medical care, enabling them to live at home with their families. However, patients with SMID have difficulty with verbal communication and have limited physical movements. Therefore, they are often unable to communicate the extent of their distress or changes in their condition. This is one factor that makes it difficult for patients' families and caregivers to interact with patients with SMID.

Nursing families understand their children's reactions through daily interactions with their children and patients with SMID[1～3]. Nursing care is a physical, mental, and social burden on families of patients with SMID. Therefore, we are working on the development of a system that can detect and inform the patient of their comfort and discomfort state by capturing using a camera, the things that the family and caregivers of patients with SMID have been observing and judging over time[4].

This is a concept that if machine learning can predict and judge unknown data, it will be possible to predict and notify the symptoms that will occur later based on the subtle reactions of patients with SMID. Therefore, we have so far collected and analyzed multiple types of data such as heart rate, breath sounds, and facial expressions in a multimodal manner[4].

First, we quantified the changes in facial muscle movements from the observed images and clarified the characteristics of facial muscle movements when feeling discomfort[5~9]. Based on these results, multiple regression analysis with heart rate as the dependent variable was considered effective for determining the presence or absence of dyspnea. Moreover, we added three cases where neither family members nor nurses were sure to predict the comfortable/unpleasant situation, focused on the situations before and after sputum suction, and conducted a multiple regression analysis for each case. As a result, independent variables such as "Outer Brow Raiser", "Lips Part", and "Eyes Closed" were extracted as three items of the Action Unit common to the four cases[10] (Table 1). In this report, we use case 1 data to create a model that can detect "unusual" cases with the highest accuracy based on these three common items.

Ⅱ. Objective

By placing the three common items of the Action Unit (AU) extracted in the previous study report[10] in the input layer, we defined a model that can accurately detect cases of "unusual" and "same as usual," and clarified the network information.

Table 1. Results of multiple regression analysis[9]

Results of multiple regression analysis

Case	*Action Unit (AU)*	*B*	*β*	*t-value*	*p*	*95%CI lower*	*95%CI upper*	*VIF*	*Adjusted R2*	*n*
1	(constant)	130.51		89.58	0.00 **	127.65	133.37		0.74	492
	Eyes Closed	-88.60	-0.63	-23.50	0.00 **	-96.01	-81.19	1.35		
	Outer Brow Raiser	-295.07	-0.30	-10.72	0.00 **	-349.16	-240.97	1.47		
	Jaw Drop	170.83	0.17	7.04	0.00 **	123.13	218.54	1.09		
	Lips Part	-16.78	-0.10	-3.83	0.00 **	-25.39	-8.18	1.25		
	Mouth Stretch	-14.89	-0.06	-2.61	0.01 **	-26.09	-3.69	1.10		
	Lid Tightener	-54.76	-0.06	-2.43	0.02 *	-98.96	-10.55	1.07		
2	(constant)	141.58		154.91	0.00 **	139.78	143.37		0.62	1564
	Eyes Closed	-53.57	-0.58	-29.15	0.00 **	-57.17	-49.96	1.58		
	Lips Part	-44.98	-0.24	-13.78	0.00 **	-51.38	-38.57	1.25		
	Outer Brow Raiser	66.23	0.19	11.11	0.00 **	54.54	77.93	1.17		
	Lip Tightener	71.49	0.11	6.48	0.00 **	49.86	93.11	1.04		
	Jaw Drop	17.38	0.13	6.19	0.00 **	11.88	22.89	1.72		
	Lip Corner Depressor	126.76	0.04	2.78	0.01 **	37.43	216.10	1.01		
3	(constant)	117.52		143.05	0.00 **	115.90	119.13		0.38	734
	Eyes Closed	-14.95	-0.48	-15.64	0.00 **	-16.83	-13.08	1.09		
	Lip Corner Puller	49.96	0.33	11.22	0.00 **	41.21	58.70	1.05		
	Outer Brow Raiser	-55.61	-0.20	-6.26	0.00 **	-73.04	-38.18	1.24		
	Lips Part	-4.57	-0.09	-2.93	0.00 **	-7.64	-1.51	1.10		
	Lip Pucker	129.80	0.09	3.07	0.00 **	46.89	212.71	1.01		
	Lid Tightener	37.29	0.09	2.99	0.00 **	12.84	61.74	1.17		
	Inner Brow Raiser	-37.87	-0.08	-2.34	0.02 *	-69.60	-6.13	1.28		
4	(constant)	106.76		190.06	0.00 **	105.65	107.86		0.73	1816
	Eyes Closed	-33.00	-0.74	-55.05	0.00 **	-34.17	-31.82	1.22		
	Lips Part	38.14	0.36	22.25	0.00 **	34.78	41.51	1.75		
	Inner Brow Raiser	-96.70	-0.12	-8.56	0.00 **	-118.85	-74.55	1.30		
	Lip Tightener	-116.59	-0.13	-10.60	0.00 **	-138.16	-95.02	1.01		
	Jaw Drop	-51.48	-0.14	-8.44	0.00 **	-63.44	-39.52	1.74		
	Lip Corner Depressor	-165.34	-0.09	-7.29	0.00 **	-209.84	-120.83	1.06		
	Outer Brow Raiser	354.09	0.08	5.15	0.00 **	219.23	488.95	1.68		
	Lip Pressor	-2346.30	-0.05	-2.97	0.00 **	-3893.16	-799.44	1.65		

forward, dependent variables Heart rate (The heart rate here is the pulse rate measured by a pulse oximeter.)
*$p<0.05$. **$p<0.01$. n(The number of data). VIF (Variance inflation factor)

Ⅲ. Methods

The study was approved by the research ethics review committee of the affiliated institution (approval numbers : 2019034 and 2019045) and was performed with the consent of the facility. We distributed an explanatory note, a cooperation consent form, and a self-addressed stamped envelope to the caregivers of patients with SMID (Oshima's classification 1 to 4) who visited the research cooperation facility, explained the necessary items, and recruited research participants.

1 Data collection period

From November 2019 to the end of February 2020.

2 Data collection methods

Before collecting data on patients with SMID, we confirmed the physical condition of patients with SMID and points to keep in mind with their families and conducted an interview about their experiences in raising children. After participating in training, health care, and child development support activities in research cooperation facilities and understanding the characteristics of patients with SMID, we collected data while paying attention to safety. In addition, interviews with nursing care personnel and families, and observations of patients with SMID were carried out with the support of medical specialists, while examining methods suited to the individuality of patients with SMID[5].

Heart rate was recorded every second with a pulse oximeter Listox 2 model 3150BLE (hereinafter referred to as the pulse oximeter). The movement of facial muscles was captured with a web camera and analyzed with Face Reader 8, and 20 items of facial muscle movement data were extracted as numerical values. This analysis software can detect 500 facial points and capture minute changes in facial muscles; therefore, it has the ability to detect facial muscle movements and blood flow that are invisible to humans. The movement of the facial muscles was digitized in the range of 0-1, with 1 being the maximum intensity. Breath sounds were collected using an electronic stethoscope before and after sputum suction and during postural changes during sleep, taking care not to disturb the sleep of the patients with SMID. Auscultation was performed by placing sensors on the left and right sides of the anterior chest and the left and right interscapular regions of the back, and lung sounds during breathing were collected for approximately 1 minute. The data were compared with the frequency spectra subjected to a fast Fourier transform. In addition, all the sensing devices were connected to the same computer and synchronized by setting the time. After the data were analyzed, they were outputted as comma-separated values (CSV) data.

3 Overview of a research collaborator

The research participant was an 11-year-old boy with Oshima's classification 1 cerebral palsy. This patient had an MD-SMID score of 37, requiring constant use of a pulse oximeter and sputum suction, and the duration of home care was over 10 years. Therefore, this boy could judge discomfort based on experience. The length of the scenes used for data analysis was 9 minutes in total, 6 minutes immediately after suction of retained sputum, and 3 minutes after 15 minutes.

4 Analysis method

Analysis by a three-layer neural network was performed in the following procedure.

1) The video captured by the web camera was analyzed with the facial expression analysis software Face Reader 8, and numerical data of 20 items were extracted 15 times per second. The total number of samples, 3556, was divided into 7:3 for learning and testing.
2) Three items, "Outer Brow Raiser," "Lips Part," and "Eyes Closed," were placed in the input layer. Before that, we compared the Area Under the Curve (AUC) values of multiple independent variables and evaluated the strength of their association with "unusual" (outcome). The results are shown in Figure 1 (ROC curve) and Table 2 (AUC). Here, ROC is an acronym for Receiver Operating

Characteristic, and refers to the curve obtained when sensitivity is plotted on the vertical axis and (1.0-specificity) on the horisontal axis.

3) The output layer consisted of two items, "unusual" and "same as usual".

4) The number of units in each hidden layer was set to 2 to 4.

5) The hidden layer activation functions were; "Method 1: sigmoid function" and "Method 2: hyperbolic tangent function".

6) The activation function of the output layer was the sigmoid function.

7) The learning method was batch learning.

5 Ethical considerations

Since patients with SMID and study collaborators also have complications, such as respiratory depression associated with increased muscle tone caused by unfamiliar stimuli, induction of seizure, and the associated respiratory depression or respiratory disorders, infectious diseases can lead to exacerbation of respiratory disorders and life-threatening crises. In addition, patients with SMID have linguistic communication disorders and cannot complain of poor physical condition by themselves. Therefore, we paid attention to the changes in their physical conditions and facial expressions and attended the training, care for daily life, or child development support activities in the facilities in advance after obtaining consent from their family. Understanding the characteristics of patients with SMID in this way, we paid attention to safety during data collection. In addition, we examined the methods that suit the individuality of patients with SMID through hearing of specialists and families and observation of patients with SMID, with support from pediatric cranial nerve specialists. At the stage of request for study collaboration, we explained the purpose of the study in writing and verbally to the subjects; guaranteed free participation and withdrawal, which does not lead to any disadvantage; and explained the guarantee of anonymity and a method of publication of results before obtaining consent from the subjects.

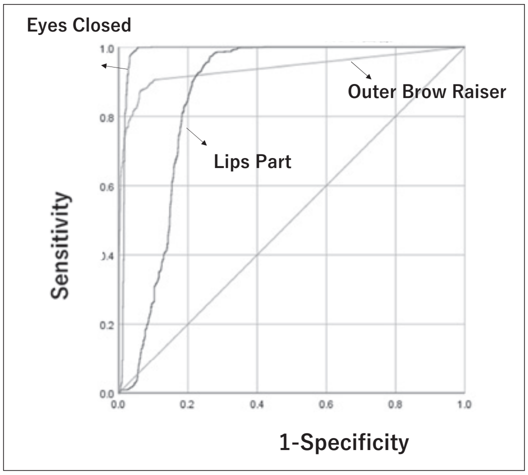

Figure 1. ROC curve of Action Unit 3 items

Ⅳ. Results

Three items, "Outer Brow Raiser", "Lips Part", and "Eyes Closed", were placed in the input layer, and two variables, "unusual" and "same as usual", were placed in the output layer. An analysis was performed using a 3-layer neural network with two to four units. Table 3 lists the number of units in the hidden layer and the percentage of correct answers for methods 1 and 2. Table 4 shows the cross-entropy loss and percentage of incorrect predictions. Figure 4 shows the ROC curve.

Ⅴ. Discussion

The three common AU items obtained in the previous research report[10] were placed in the input layer, and the analysis was performed using a three-layer neural network. We classified the results, compared the ROC curves, AUC values, and cross-entropy errors, and considered the most accurate network information.

Table 2. AUC value of Action Unit 3 item

Action Unit	AUC
Outer Brow Raiser	0.937
Lips Part	0.858
Eyes Closed	0.984

Table 3. The number of units in the hidden layer of methods 1 and 2 and the percentage of correct answers

Method	Hidden layer1 Unit count	Hidden layer2 Unit count		sample	Learning		Testing	
					Unusual	Same as usual	Unusual	Same as usual
1(1)	2	2	Prediction value	Unusual	590	3	285	0
				Same as usual	3	1860	0	815
				Percentage of correct answers	99.5%	99.8%	100.0%	100.0%
1(2)	2	3	Prediction value	Unusual	605	4	271	0
				Same as usual	2	1871	0	803
				Percentage of correct answers	99.7%	99.8%	100.0%	100.0%
1(3)	3	2	Prediction value	Unusual	602	4	274	1
				Same as usual	1	1862	1	811
				Percentage of correct answers	99.8%	99.8%	99.6%	99.9%
1(4)	3	3	Prediction value	Unusual	578	13	268	2
				Same as usual	25	1853	7	810
				Percentage of correct answers	95.9%	99.3%	97.5%	99.8%
1(5)	4	4	Prediction value	Unusual	603	4	273	1
				Same as usual	0	1862	2	811
				Percentage of correct answers	100.0%	99.8%	99.3%	99.9%
2(1)	2	2	Prediction value	Unusual	595	16	253	9
				Same as usual	16	1889	14	764
				Percentage of correct answers	97.4%	99.2%	94.8%	98.8%
2(2)	2	3	Prediction value	Unusual	592	25	270	7
				Same as usual	9	1896	7	750
				Percentage of correct answers	98.5%	98.7%	97.5%	99.1%
2(3)	3	2	Prediction value	Unusual	619	1	257	0
				Same as usual	2	1870	0	807
				Percentage of correct answers	99.7%	99.9%	100.0%	100.0%
2(4)	3	3	Prediction value	Unusual	606	1	270	2
				Same as usual	2	1872	0	803
				Percentage of correct answers	99.7%	99.9%	100.0%	99.8%
2(5)	4	4	Prediction value	Unusual	603	4	273	1
				Same as usual	0	1862	2	811
				Percentage of correct answers	100.0%	99.8%	99.3%	99.9%

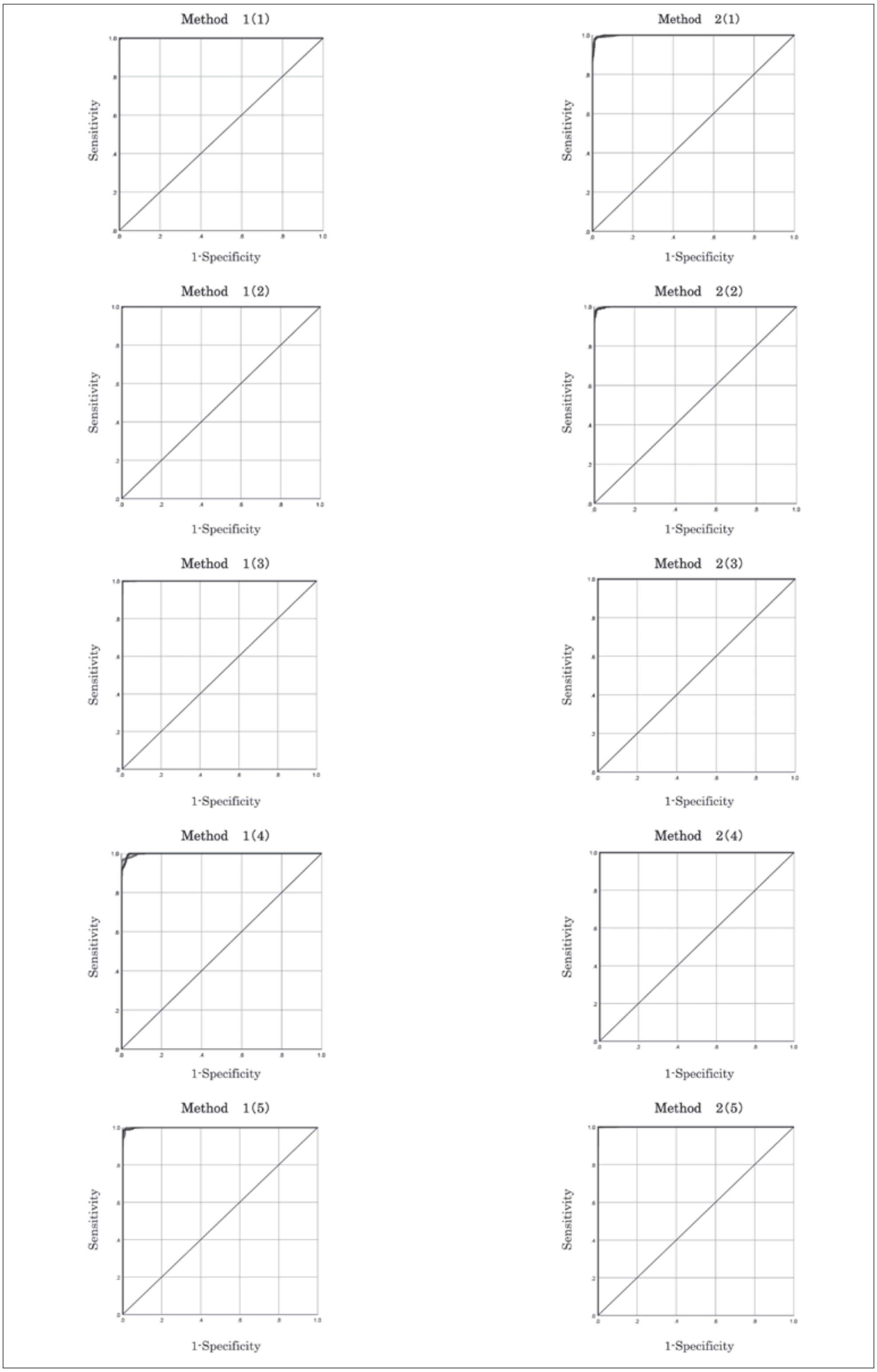

Figure 2. Differences in the ROC curves

Table 4. Cross-entropy loss and percentage of incorrect predictions

Method	Hidden layer1 Unit count	Hidden layer2 Unit count	Learning		Testing		Activation function	
			Cross-entropy Loss	percentage of incorrect predictions	Cross-entropy Loss	percentage of incorrect predictions	Hidden layer	Output layer
1(1)	2	2	19.0	0.0	2.8	0.0%	Sigmoid function	Sigmoid function
1(2)	2	3	15.8	0.0	1.7	0.0%		
1(3)	3	2	29.9	0.0	4.1	0.2%		
1(4)	3	3	160.3	0.0	49.3	0.8%		
1(5)	4	4	90.6	0.0	25.9	0.9%		
2(1)	2	2	92.2	0.0	63.2	2.2%	Hyperbolic tangent function	
2(2)	2	3	80.6	0.0	35.5	1.4%		
2(3)	3	2	11.2	0.0	2.1	0.0%		
2(4)	3	3	10.5	0.0	4.8	0.2%		
2(5)	4	4	35.8	0.0	5.9	0.3%		

1 Percentage of correct answers in learning and testing

In all the methods, we were able to maintain an accuracy of 90% or more for both learning and testing. In methods 1(1), 1(2), and 2(3), the test samples were classified correctly.

2 Area Under the Curve

Sensitivity is how much of the data that is "unusual" is judged to be "unusual," and the effectiveness of the model can be judged by analyzing this sensitivity. Additionally, because the effectiveness of the model is reflected in the area under the ROC curve, it is possible to perform a comprehensive evaluation of the test using the AUC. The AUC value is the area under the ROC curve, and the closer the AUC value is to 1, the better the classification model. All eight methods listed in Table 3 were considered highly accurate.

3 Cross-entropy error

In machine learning, weighting is performed and learning proceeds. Cross-entropy error was used to assess the accuracy of the model. When comparing the distribution of the supervised data and the distribution of the prediction data, the smaller the difference, the closer the cross-entropy error is to zero, and the larger the difference, the larger the cross-entropy error. To create a highly accurate model, it is necessary to adjust the weights to reduce cross-entropy error. Therefore, when comparing the cross-entropy error values, method 2(3) yielded the lowest results. Regarding method 2(5), the percentage of correct answers in table 3 was over 99% for both learning and testing, and the ROC curve also suggested that the accuracy was high, but the cross-entropy error was considerably larger than the others.

4 Summary

The most accurate prediction was possible when the number of units in the first layer of the hidden layer was three, the number of units in the second layer of the hidden layer was two, the hidden layer activation function was a hyperbolic tangent function, and the output layer activation function was a sigmoid function.

5 Future tasks

We will examine whether this model can be applied not only before and after sputum expectoration but also in other situations. We will also collect large amounts of stable and continuous data to improve the accuracy of machine learning. For this purpose, it is necessary to improve the equipment so that the data can be collected easily and accurately.

Ⅵ. Conclusion

In the system model developed in this study that detects and notifies patients with SMID abnormalities, we examined the abnormality detection accuracy based on changes before and after sputum expectoration. In a

3-layer neural network, of which the input layer consists of 3 neurons of "Outer Brow Raiser, " "Lips Part, " and "Eyes Closed, " the hidden layer consists of the first hidden layer of three neurons and the second hidden layer of two neurons, and the output layer consists of two neurons, and when the hidden layer activation function is the hyperbolic tangent function and the output layer activation function is the sigmoid function, we found that the classification can be performed with the best accuracy.

There are no conflicts of interest to disclose regarding this article.

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