Deep Learning-Based Functional Independence Measure Score Prediction After Stroke in Kaifukuki (Convalescent) Rehabilitation Ward Annexed to Acute Care Hospital

Masahito Katsuki 1, 2, Norio Narita 1, Dan Ozaki 1, Yoshimichi Sato 1, Wenting Jia 1, Takeko Nishizawa 1, Ryuzauburo Kochi 1, Kanako Sato 1, Kokoro Kawamura 1, Naoya Ishida 1, Ohmi Watanabe 1, Siqi Cai 1, Shinya Shimabukuro 1, Iori Yasuda 1, Kengo Kinjo 1, Kenichi Yokota 1

1. Neurosurgery, Kesennuma City Hospital, Kesennuma, JPN
2. Neurosurgery, Itoigawa General Hospital, Itoigawa, JPN

Corresponding author: Norio Narita, naritanorio1111@gmail.com

Abstract

Introduction
Prediction models of functional independent measure (FIM) score after kaifukuki (convalescent) rehabilitation ward (KRW) are needed to decide the treatment strategies and save medical resources.

Methods
Of the 559 consecutive stroke patients, 122 patients were transferred to our KRW. We divided our 122 patients’ data randomly into halves of training and validation datasets. Prediction One made three prediction models from the training dataset using (1) variables at the acute care ward admission, (2) those at the KRW admission, and (3) those combined (1) and (2). The models’ determination coefficients ($R^2$), correlation coefficients ($r_s$), and residuals were calculated using the validation dataset.

Results
Of the 122 patients, the median age was 71, length of stay (LOS) in acute care ward 23 (17-30) days, LOS in KRW 53 days, total FIM scores at the admission of KRW 85, those at discharge 108. The mean FIM gain and FIM efficiency were 19 and 0.417. All patients were discharged home. Model (1), (2), and (3)’s $R^2$ were 0.794, 0.970, and 0.972. Their mean residuals between the predicted and actual total FIM scores were -1.56±24.6, -4.49±17.1, and -2.69±15.7.

Conclusion
Our FIM gain and efficiency were better than national averages of FIM gain 17.1 and FIM efficiency 0.187. We made DL-based total FIM score prediction models, and their accuracies were superior to those of previous statistically calculated ones. The DL-based FIM score prediction models would save medical costs and perform efficient stroke and rehabilitation medicine.

Categories: Neurology, Neurosurgery, Public Health
Keywords: artificial intelligence (AI), deep learning (DL), functional independent measure (FIM), kaifukuki (convalescent) rehabilitation ward (KRW), stroke, prediction model, prediction one, sony network communications inc. Japan

Introduction
In Japan, stroke is the third leading cause of death and the second leading cause of long-term disability. Japan started a characteristic rehabilitation system in 2000 called kaifukuki (convalescent) rehabilitation wards (KRWs). KRW is incorporated into the Japanese medical insurance system, and The Japan Ministry of Health, Labour, and Welfare define KRWs as the essential inpatient rehabilitation system. Stroke patients are eligible for the KRW. They can undergo rehabilitation up to 150 days and 3 hours per day of rehabilitation, including physical, occupational, and speech therapy, in the KRW. There are over 60 KRW beds per 100,000 individuals, comprising 4.6% of the total Japanese hospital beds, and the number of KRW is increasing [1].

According to the Japanese Guidelines for the Management of Stroke 2015, rehabilitation should be performed to predict functional prognosis, hospital stay, and outcome-based activities of daily living, functional disability, and comorbidities [2]. Also, the KRW’s quality should be maintained, and we should save the limited medical resources. Since 2017, the functional independence measure (FIM) score [3] has
We also investigated the modified Rankin Scale scores when the patients were transferred to the KRW. The Japan) was used through the methods described previously [34]. Controlling nutritional status scores to assess the patients' nutritional status on admission in the acute neurosurgical ward. Albumin, lymphocyte, and total cholesterol are known factors for protein, blood glucose, haemoglobin A1c, haemoglobin levels, and white blood cell and lymphocyte counts of chronic kidney diseases, orthopaedic diseases, or cancer). Glasgow Coma Scale (GCS) and National Institutes of Health Stroke Scale scores on admission were also investigated. We also measured triglycerides, total cholesterol, high-density lipoprotein cholesterol, low-density lipoprotein cholesterol, albumin, C-reactive protein, blood glucose, haemoglobin A1c, haemoglobin levels, and white blood cell and lymphocyte counts in the acute neurosurgical ward. Albumin, lymphocyte, and total cholesterol are known factors for controlling nutritional status scores to assess the patients’ nutritional status [26]. As radiological findings, we investigated temporal muscle thickness (TMT) (mm) as an indicator of systemic skeletal muscle mass [27-54] based on the results of the CT at admission. SYNAPSE V 4.1.5 imaging software (Fujifilm Medical, Tokyo, Japan) was used through the methods described previously [52,53].

We also investigated the modified Rankin Scale scores when the patients were transferred to the KRW. The
LOS in the acute care ward and KRW were also investigated. Barthel Index (BI) at the admission of acute care ward, FIM score at admission to KRW and the discharge of KRW, FIM gain, and FIM efficiency were also collected, and the total FIM score at discharge was defined as an outcome in this study. There were no missing values.

Making prediction model by Prediction One

We used Prediction One framework to make the prediction models. We divided our 122 patients’ data randomly into 61 patients training dataset and 61 patients validation dataset. Prediction One read the training data and automatically performed 5-folds cross-validation. Prediction One automatically adjusted and optimized the easy to process variables statistically and mathematically and select appropriate algorithms with ensemble learning. Prediction One made the best prediction model by an artificial neural network with internal cross-validation. The details are trade secrets and could not be provided.

We let the Prediction One framework make three prediction models using training dataset; (1) using 49 variables acquired only at the admission of acute care ward, (2) using 40 variables, including FIM scores, which could be known only at the admission of KRW, and (3) using all 70 variables acquired both at the admissions of acute care and KRW. The determination coefficient ($R^2$) and strong variables of each model were automatically calculated. Then, we performed validation using the validation datasets. Correlation coefficients ($r$) and residuals between the predicted and actual total FIM scores were calculated to evaluate the models’ accuracy.

Statistical analysis

Results are basically shown as median (interquartile range). The difference between the training dataset and the external validation dataset was tested appropriately using the Mann-Whitney U test, Fisher’s exact test, or Pearson’s chi-square test. Univariate analysis on the association between each variable and total FIM score at the discharge of KRW was also performed. We could not perform multiple regression due to the small sample size and non-normal distribution of variables. A two-tailed $p < 0.05$ was considered statistically significant. We calculated $r$ and these $p$ values using SPSS software version 24.0.0. (IBM, New York, USA).

Results

Clinical characteristics

The clinical characteristics of the 559 stroke patients (421 CI, 98 ICH, 40 SAH; 224 women and 335 men) are summarized in table 1. The median (interquartile range) age was 77 (69-83), and LOS in the acute care ward 15 (7-26). Regarding discharge destinations, 205 patients were discharged home, 122 patients were transferred to KRW, 81 nursing facilities, 79 long-term hospitals, and 72 patients died.
All stroke (n = 559) | CI (n = 421, 75%) | ICH (n = 98, 18%) | SAH (n = 40, 7%)
---|---|---|---
Age (median, interquartile range) | 77 (69-83) | 77 (70-83) | 79 (69-83) | 66 (59-83)
32-50 y.o. | 17 (3%) | 10 (2%) | 5 (5%) | 2 (5%)
51-65 y.o. | 68 (12%) | 39 (9%) | 13 (13%) | 16 (40%)
66-75 y.o. | 165 (30%) | 139 (33%) | 17 (18%) | 9 (21%)
76-85 y.o. | 224 (40%) | 163 (39%) | 51 (52%) | 11 (27%)
86-95 y.o. | 79 (14%) | 66 (16%) | 12 (12%) | 1 (2%)
95- y.o. | 6 (1%) | 4 (1%) | 0 | 2 (5%)
Women: Men (Women%) | 224: 335 (40%) | 167: 254 (40%) | 36: 62 (37%) | 21: 19 (53%)
Discharge destination from the acute ward
Home | 205 (37%) | 162 (38%) | 32 (33%) | 11 (27%)
KRW | 122 (22%) | 73 (17%) | 33 (33%) | 17 (43%)
Nursing facility | 81 (14%) | 62 (15%) | 17 (17%) | 2 (5%)
Long term hospital | 79 (14%) | 64 (16%) | 13 (13%) | 2 (5%)
Dead | 72 (13%) | 60 (14%) | 4 (4%) | 8 (20%)
LOS in an acute ward (days) (median, interquartile range) | 15 (7-26) | 19 (7-45) | 21 (12-44) | 10 (1-39)

**TABLE 1: Characteristics of all stroke patients**

KRW; kalifukuki (convalescent) rehabilitation ward, LOS; length of stay.

Table 2 shows the treatment detail of 122 patients (67 CI, 42 ICH, and 15 SAH) who were transferred to KRW. Thirty-nine (32%) of the 122 patients underwent aggressive treatment like intravenous tissue plasminogen activator, thrombectomy, hematoma removal surgery, or aneurysm ligation, rather than only medication.

**TABLE 2: Stroke types and treatment of patients who underwent KRW**

ACoA; anterior communicating artery, ACD; distal part of anterior cerebral artery, A-to-A; artery to artery embolism, ATBI; atherothrombotic brain infarction, BA; basilar artery, BAD; branch atheromatous disease, CI; cerebral infarction, CE; cardiogenic embolism, C; cerebral infarction, ESUS; embolic stroke of undetermined sources, ICA; internal carotid artery, ICH; intracerebral hemorrhage, LI; lacunar infarction, MCA; middle cerebral artery, SAH; subarachnoid hemorrhage, t-PA; tissue-plasminogen activator; VAD; vertebral artery dissection.

Table 3 shows the characteristics of the 122 patients (49 women and 73 men). The median age was 71 (64-79), LOS in acute care ward 23 (17-30) days, LOS in KRW 53 (35-92) days, total FIM scores at admission of
KRW 85 (57-100), those at discharge 108 (86-118), FIM gain 19 (8-89), and FIM efficiency 0.271 (0.147-0.561). All 122 patients were discharged home. The mean FIM gain and FIM efficiency were 19 and 0.417, although they were not with a normal distribution (Table 3). Age (r = -0.487, p < 0.001), LOS in KRW (r = -0.501, p < 0.001), body weight (r = 0.322, p < 0.001), GCS score at admission (r = 0.350, p < 0.001), BI at admission of acute care ward (r = 0.435, p < 0.001), total FIM score at admission of KRW (r = 0.874, p < 0.001) were significantly associated with total FIM score at discharge of KRW in univariate analyses.

|                          | Total (n = 122) | CI (n = 67) | ICH (n = 42) | SAH (n = 13) |
|--------------------------|----------------|------------|-------------|-------------|
| Age (median, interquartile range) | 71 (64-79)     | 53 (35-92) | 70 (65-78)  | 65 (67-75)  |
| Women: Men (Women%)      | 49:73          | 24:43      | 19:23       | 6:7         |
| Body mass index (kg/m²)  | 22.5 (20.8-25.0) | 22.5 (20.8-25)  | 22.3 (19.6-24.4) | 22.8 (21.1-24.5) |
| Past history             |                |            |             |             |
| Presence of hypertension | 89 (73%)       | 46 (69%)   | 33 (76%)    | 10 (77%)    |
| Presence of diabetes mellitus | 29 (24%)     | 19 (28%)   | 9 (21%)     | 1 (8%)      |
| Presence of sydrlipidemia | 30 (26%)       | 17 (25%)   | 7 (17%)     | 6 (46%)     |
| History of smoking       | 62 (51%)       | 35 (52%)   | 20 (48%)    | 7 (54%)     |
| History of massive alcohol consumption | 35 (29%)     | 21 (31%)   | 10 (24%)    | 4 (31%)     |
| Presence of chronic kidney disease | 10 (8%)     | 5 (7%)     | 4 (10%)     | 1 (8%)      |
| Presence of orthopedic disease | 15 (12%)    | 8 (12%)    | 6 (14%)     | 1 (8%)      |
| Presence of malignant tumor | 7 (8%)        | 5 (7%)     | 0           | 2 (15%)     |
| Glasgow Coma Scale on admission | 14 (14-15)   | 15 (14-15) | 14 (13-14) | 14 (10-15)  |
| NIHSS on admission        | 5 (3-11)       | 5 (3-10)   | 8 (3-15)    | -           |
| Barthel index on admission | 23 (0-41)     | 25 (5-45)  | 5 (0-30)    | 5 (0-35)    |
| Laboratory test           |                |            |             |             |
| Triglycerides (mg/dL)     | 99 (68-144)    | 105 (73-148)| 88 (65-143)| 96 (81-127) |
| Total cholesterol (mg/dL) | 191 (169-222)  | 186 (168-214)| 199 (166-229)| 203 (186-223)|
| High-density lipoprotein cholesterol (mg/dL) | 49.9 (42.5-68.9)| 48.1 (42.2-64.0)| 48.6 (45.5-75.0)| 71.0 (48.1-75.0)|
| Low-density lipoprotein cholesterol (mg/dL) | 114 (93-137)  | 115 (94-137)| 113 (93-139)| 116 (93-137) |
| Albumin (g/dL)            | 4.3 (4.0-4.5)  | 4.3 (4.0-4.6)| 4.3 (4.0-4.5)| 7.3 (6.8-7.5)|
| C-reactive protein (mg/dL) | 0.2 (0.1-0.4) | 0.2 (0.1-0.4)| 0.2 (0.1-0.5)| 0.2 (0.1-0.3)|
| Blood glucose (mg/dL)     | 133 (108-165)  | 130 (106-168)| 133 (112-159)| 144 (122-163)|
| HbA1c (%)                 | 5.8 (5.5-6.4)  | 5.9 (5.5-6.6)| 5.9 (5.4-6.3)| 5.5 (5.4-5.7)|
| White blood cell count (μL) | 7400 (6000-9900)| 7150 (5750-8800)| 7750 (6000-10400)| 8800 (7200-10300)|
| Hemoglobin (g/dL)         | 13.8 (12.6-15.4)| 13.8 (12.6-15.9)| 13.5 (12.4-15.2)| 13.9 (13.3-15.3)|
| Lymphocyte count (μL)     | 1611 (1198-2159)| 1570 (1185-2025)| 1540 (1309-2240)| 2083 (1627-3313)|
| Temporal muscle thickness (mm) | 4.6 (3.6-5.9) | 4.5 (3.7-5.7) | 4.8 (3.7-5.9) | 5.0 (3.5-6.8) |
| Modified Rankin Scale when transferred | 3 (3-4)       | 3 (3-4)    | 4 (3-5)     | 2 (2-4)     |
| LOS in an acute ward (days) (median, interquartile range) | 23 (17-30)     | 23 (17-29) | 22 (17-29)  | 30 (26-33)  |
| FIM scores (median, interquartile) admission discharge admission discharge admission discharge admission discharge
### Table 3: Detailed characteristics of patients who were hospitalized in KRW

| Table 3 | Detailed characteristics of patients who were hospitalized in KRW |
|---------|---------------|
| CI; cerebral infarction, FIM; functional independent measure, ICH; intracerebral hemorrhage, KRW; kaifukuki (convalescent) rehabilitation ward, LOS; length of stay, NIHSS; National Institutes of Health Stroke Scale, SAH; subarachnoid hemorrhage, SD; standard deviation. |

**Range** to KRW of KRW to KRW of KRW to KRW of KRW to KRW of KRW

**Self-care**
- **Eating**: 6 (5-7) 7 (5-7) 6 (5-7) 7 (5-7) 5 (4-6) 6 (5-7) 7 (5-7) 7 (7-7)
- **Grooming**: 5 (4-7) 7 (5-7) 5 (4-7) 7 (5-7) 5 (3-5) 6 (5-7) 7 (4-7) 7 (7-7)
- **Bathing**: 4 (1-5) 5 (4-7) 4 (1-5) 5 (5-7) 2 (1-4) 5 (3-5) 3 (1-6) 7 (6-7)
- **Dressing-Upper body**: 5 (2-7) 7 (5-7) 5 (4-7) 7 (6-7) 4 (2-6) 6 (4-7) 6 (3-7) 7 (7-7)
- **Dressing-Lower body**: 5 (1-7) 6 (5-7) 5 (4-7) 7 (6-7) 4 (1-5) 6 (4-7) 5 (3-7) 7 (7-7)
- **Toileting**: 6 (2-6) 6 (6-7) 6 (4-7) 7 (5-7) 4 (1-6) 6 (4-7) 7 (5-7) 7 (6-7)
- **Sphincter Control**
  - **Bladder Management**: 5 (2-7) 7 (5-7) 7 (4-7) 6 (5-7) 4 (1-6) 6 (4-7) 7 (3-7) 7 (7-7)
  - **Bowel Management**: 5 (4-6) 5 (5-7) 5 (5-6) 6 (5-7) 4 (2-6) 5 (5-6) 5 (4-5) 5 (5-6)

**Transfer**
- **Bed, Chair, Wheelchair**: 5 (3-7) 6 (5-7) 5 (5-7) 6 (6-7) 5 (2-6) 5 (5-7) 7 (4-7) 7 (7-7)
- **Toileting**: 5 (3-6) 6 (5-7) 6 (5-7) 5 (4-7) 4 (2-5) 6 (5-7) 7 (4-7) 7 (7-7)
- **Tub, Shower**: 1 (1-5) 5 (1-6) 1 (1-5) 6 (5-7) 5 (1-6) 4 (1-5) 1 (1-2) 6 (5-6)

**Locomotion**
- **Walk/Wheelchair**: 5 (1-6) 6 (5-7) 5 (4-6) 6 (5-7) 1 (1-5) 5 (4-7) 5 (4-7) 7 (7-7)
- **Stairs**: 1 (1-5) 5 (4-6) 1 (1-5) 5 (5-6) 1 (1-1) 5 (3-5) 3 (1-5) 5 (5-6)
- **Motor Subtotal Score**: 62 (36-72) 80 (62-87) 66 (51-75) 81 (67-87) 45 (22-65) 73 (55-81) 69 (47-77) 87 (82-88)

**Communication**
- **Comprehension**: 5 (3-6) 6 (5-7) 5 (4-6) 6 (5-7) 5 (3-6) 6 (5-7) 5 (2-7) 7 (5-7)
- **Expression**: 5 (3-6) 6 (5-7) 5 (4-6) 7 (5-7) 4 (3-6) 6 (5-7) 4 (3-7) 7 (5-7)

**Social Cognition**
- **Social Interaction**: 6 (4-6) 7 (6-7) 6 (5-6) 7 (6-7) 5 (4-6) 6 (6-7) 5 (3-6) 7 (6-7)
- **Problem Solving**: 4 (2-5) 5 (3-6) 5 (2-5) 5 (4-6) 2 (2-6) 5 (5-6) 5 (2-5) 5 (5-7)
- **Memory**: 4 (3-6) 6 (4-7) 5 (3-6) 6 (5-7) 3 (2-5) 5 (4-6) 5 (2-5) 5 (4-6)
- **Cognitive Subtotal Score**: 23 (17-29) 29 (23-32) 25 (18-29) 30 (24-32) 20 (14-26) 28 (21-31) 22 (13-30) 30 (26-33)

**Total FIM Score**
- **LOS in KRW (days) (median, interquartile range)**: 53 (35-92) 47 (35-68) 66 (45-117) 36 (32-67)
- **FIM gain (median)**: 19 (8-89) 16 (7-25) 25 (15-31) 16 (12-24)
- **FIM efficiency (median)**: 0.271 (0.147-0.561) 0.286 (0.133-0.589) 0.254 (0.146-0.423) 0.400 (0.105-0.735)
- **FIM gain (mean±SD)**: 19±19 16±11 23±17 16±12
- **FIM efficiency (mean±SD)**: 0.417±0.652 0.456±0.820 0.308±0.280 0.457±0.385

**Model development and validation**

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There were no significant differences in the variables between the training and validation datasets. Prediction One produced each prediction model in less than two minutes. The R$^2$ of each model were described in Table 4. Model (1), using 49 variables acquired only at the acute care ward admission, had an R$^2$ of 0.794. Its r and mean ± standard deviation of residuals between the predicted and actual total FIM scores were 0.372 (95% confident interval 0.120-0.578) and -1.56 ± 24.6. Model (2) using 40 variables acquired only at the admission of KRW had R$^2$ of 0.970, and its r and residuals were 0.789 (0.788-0.790) and -4.49 ± 17.1. Model (3) using all 70 variables acquired both in the acute and KRW had R$^2$ of 0.974, and its r and residuals were 0.810 (0.810-0.811) and -2.69 ± 15.7. The results are compared to those of previous reports [4-15] (Table 4).

| Year | Author | Number of variables | R$^2$ | institutions | Number of patients | Mean age | Mean LOS in the acute ward (days) | Mean LOS in the KRW (days) | Validation | R$^2$ of validation | r of validation | mean residuals±SD |
|------|--------|---------------------|------|--------------|-------------------|---------|---------------------------------|--------------------------|-------------|---------------------|-----------------|------------------|
| 1997 | Liu [4] | 1                   | 0.798| single       | 106               | 56.5    | 83                              | 105.5                    | -           |                     |                 |                  |
| 2000 | Tsuji [5] | 3                  | 0.64 | multiple     | 190 training + 116 validation | 61   | 47.3                           | 90.9                     | +           | 0.68                |                 |                  |
| 2001 | Inouye [6] | 1                  | 0.57 | single       | 464               | 60      | 74                             | 116                      | -           |                     |                 |                  |
| 2001 | Inouye [6] | 4                  | 0.76 | single       | 464               | 60      | 74                             | 116                      | -           |                     |                 |                  |
| 2005 | Sonoda [7] | 4                  | Not described | single | 87 training + 44 validation | 63.4  | 81.3                           | 154.3                    | +           | 0.88                | 8.06 ± 6.29     |                  |
| 2016 | Tsuchiya [8] | 3                  | 0.30 | single       | 108               | 66.8    | 45.5                           | 99.9                     | -           |                     |                 |                  |
| 2016 | Senda [9] | 5                  | 0.591| single       | 520               | 72.8    | 32.8                           | 55.4                     | -           |                     |                 |                  |
| 2016 | Nishioka [10] | 8                 | 0.603| single       | 897               | 71.6    | 21 (median)                    | 122 (median)             | -           |                     |                 |                  |
| 2017 | Shiraishi [11] | 3                | 0.776| single       | 108 (including not only stroke patients) | 80.5 | Not described                  | 65.2                    | -           |                     |                 |                  |
| 2019 | Matsushita [12] | 3                | 0.673| single       | 267               | 72.5    | 24                             | 105.1                    | -           |                     |                 |                  |
| 2019 | Nishioka [13] | 6                | 0.742| multiple     | 5549 (including not only stroke patients) | 82   | Within 2 months.               | 72                       | -           |                     |                 |                  |
| 2019 | Yoshimura [14] | 6                | 0.719| single       | 276               | 74.9    | 15                             | 99.9                     | -           |                     |                 |                  |
| 2019 | Senda [15] | 2                  | 0.691| single       | 371               | 72.9    | 31.4                           | 79.7                     | -           |                     |                 |                  |
| 2021 | Ours | 49                | 0.794| single       | 61 training + 61 validation | 69.4 | 24.3                           | 53                       | +           | 0.372 (0.120-0.578) | -1.56 ± 24.6     |                  |
TABLE 4: Previous prediction models for total FIM score at discharge

FIM; functional independent measure, KRW; kaifukuki (convalescent) rehabilitation ward, LOS; length of stay, r; correlation coefficients, R²; determination coefficients

The more robust variables of each model are listed in Table 5. In model (1), TMT, lymphocyte count, low-density lipoprotein cholesterol level, total BI score, and haemoglobin level had enormous effects on the outcome. In model (2), Age, FIM (bowel management), TMT, FIM (toileting), and LOS in the acute care ward were important. In model (3), Total FIM scores, subtotal cognitive FIM score, FIM (comprehension), subtotal motor FIM score, and blood glucose levels were meaningful, in order.

TABLE 5: Stronger variables of each model provided by Prediction One (Sony Network Communications Inc., Japan)

BI; Barthel index, FIM; functional independent measure, KRW; kaifukuki (convalescent) rehabilitation ward, LOS; length of stay, NIHSS; National Institutes of Health Stroke Scale

Discussion

We made prediction models for the total FIM score at the discharge of KRW in our hospital. We made three models; (1) using information gained at the admission of acute care ward, (2) using information gained at the admission of KRW, and (3) combined (1) and (2). DL-based models (2) and (3) had good accuracies, and we also performed validation, despite our small dataset. This is the first report on creating DL-based prediction models of total FIM scores at the discharge of KRW.

KRW annexed to acute care hospital

Our hospital was rebuilt in 2017, and KRW was newly annexed. Until then, patients had been transferred to the other hospitals’ KRWs, but it took more than a month from the stroke onset to transfer. Since the new hospital, the transfer to our KRW from the stroke onset has been shortened to 23 days. Furthermore, the mean FIM gain of 19 and the mean FIM efficiency of 0.417 is higher than those of national averages of 17.1
This may be because the staff in the acute care ward and those in KRW work closely together and frequently held meetings with patients and their families. Sharing the information on patients' comorbidities, treatment status, and rehabilitation progress will allow us to smooth transfer. This openness is one of the advantages of our hospital.

In our hospital, all patients were discharged home because we only permitted the transfer to KRW for patients who might have the potential to live independently with/without families' support or those who would not live independently or bed-ridden but whose families committed to providing in-home care. We decided on these determinations after around 1-2 weeks after onset. Whether it is socially and medically right to make such an early decision needs further discussion. However, we are forced to make such early decisions to use our limited medical resources in this rural area effectively. In this situation with limited medical resources, total FIM score prediction at the discharge of KRW is essential for the effective use of limited medical resources and the decision-making of patients and their families.

Advantages of DL

Conventional cost- and time-consuming statistical analysis needs variable optimization like a logarithmic transformation to make the variables with normal distribution increase the prediction model's accuracy mathematically. It also requires the arbitrary selection of variables based on previous studies, and multivariate analysis needs 10-15 folds number of samples against the variables. Therefore, there is a risk that variables that may be important cannot be used in the statistical analysis. Even the multivariate analysis cannot be done in a small hospital with small data. Furthermore, we should do multiple imputations or listwise deletion in statistical analysis when there is missing data, leading to inaccuracy. Furthermore, we should validate the models' accuracy, but several previous reports were not validated.

DL has the potential to overcome these problems. DL develops useful models with less effort or time using the small dataset, without time-consuming variable optimization nor arbitrarily choosing variables because the DL framework automatically performs these processes. The optimal number of the variables for the DL framework is not revealed, and the DL framework sometimes finds interesting variables as necessary that has not been taken into account in the previously reported statistical models. Furthermore, the DL framework automatically uses appropriate values instead of the missing ones and calculates the best prediction model.

We then review these benefits of DL in our study. Conventionally, we could have used only six variables for statistical analysis due to the small sample size of the training dataset (n = 61). However, we could use 70 variables for making the model (S) and make a good prediction model from the small dataset. We did not need to perform variable optimization by ourselves. Furthermore, some unexpected variables, such as TMT, lymphocyte count, blood glucose level, were judged to be important in DL models. The suggestions are essential because data from the acute phase affects the total FIM score after KRW admission. What was not statistically significant in univariate analyses was deemed essential. Besides, the time needed for creating each model was less than 2 minutes. Finally, the models achieved high accuracies both in the training and validation dataset. While many reports did not conduct validation, we believe that our report is important, creating a stir about validation to present the accuracy.

Limitations of DL

First, the prediction model derived from our data cannot be applied to other institutions. The training and validation dataset must be updated to keep up with advances in medical science and surgical techniques, and medication changes. Creating a DL-based prediction model that can be used universally at any hospital will still require country-initiated or academic association-initiated collaborative research at many institutions. It may eventually require the same amount of effort as the traditional statistical model creation.

Limitation of this study

First, the sample size was small, and it is unknown how many samples are needed for DL analysis. We did not investigate the detail of rehabilitation training and how long the rehabilitation was actually performed per day for each individual. Further continuation study is needed.

Conclusions

Our hospital has the acute care ward and KRW. The FIM efficiency and LOS in the acute care ward were better than those in national averages. We easily and quickly made total FIM score prediction models using Prediction One framework. The accuracies of the prediction models were superior to those of previous statistically calculated prediction models. Even with a small single-centre dataset, DL-based total FIM score prediction models made by Prediction One can be helpful at the institution. They may be applied to daily clinical practice in the future.

Additional Information
Disclosures

Human subjects: Consent was obtained or waived by all participants in this study. Kesennuma City Hospital Ethics Committee issued approval 2020-1-5. The Kesennuma City Hospital’s Research Ethics Committee approved this study, and the approval number is 2020-1-5. We gained written informed consent for this study from all of the patients, the legally authorized representative of the patients, or the next of kin of the deceased patients. All methods were carried out in accordance with relevant guidelines and regulations (Declaration of Helsinki). Animal subjects: All authors have confirmed that this study did not involve animal subjects or tissue. Conflicts of interest: In compliance with the ICMJE uniform disclosure form, all authors declare the following: Payment/services info: All authors have declared that no financial support was received from any organization for the submitted work. Financial relationships: All authors have declared that they have no financial relationships at present or within the previous three years with any organizations that might have an interest in the submitted work. Other relationships: All authors have declared that there are no other relationships or activities that could appear to have influenced the submitted work.

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