



Original Article

Preliminary development of a prediction model for daily stroke occurrences based on meteorological and calendar information using deep learning framework (Prediction One; Sony Network Communications Inc., Japan)

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ABSTRACT

Background: Chronologically meteorological and calendar factors were risks of stroke occurrence. However, the prediction of stroke occurrences is difficult depending on only meteorological and calendar factors. We tried to make prediction models for stroke occurrences using deep learning (DL) software, Prediction One (Sony Network Communications Inc., Tokyo, Japan), with those variables.

Methods: We retrospectively investigated the daily stroke occurrences between 2017 and 2019. We used Prediction One software to make the prediction models for daily stroke occurrences (present or absent) using 221 chronologically meteorological and calendar factors. We made a prediction models from the 3-year dataset and evaluated their accuracies using the internal cross-validation. Areas under the curves (AUCs) of receiver operating characteristic curves were used as accuracies.

Results: The 371 cerebral infarction (CI), 184 intracerebral hemorrhage (ICH), and 53 subarachnoid hemorrhage patients were included in the study. The AUCs of the several DL-based prediction models for all stroke occurrences were 0.532–0.757. Those for CI were 0.600–0.782. Those for ICH were 0.714–0.988.

Conclusion: Our preliminary results suggested a probability of the DL-based prediction models for stroke occurrence only by meteorological and calendar factors. In the future, by synchronizing a variety of medical information among the electronic medical records and personal smartphones as well as integrating the physical activities or meteorological conditions in real time, the prediction of stroke occurrence could be performed with high accuracy, to save medical resources, to have patients care for themselves, and to perform efficient medicine.

Keywords: Artificial intelligence, Calendar factors, Deep learning, Meteorological factors, Stroke

INTRODUCTION

Meteorological factors were reported as the risks of stroke occurrence. In Japanese studies, it is reported that low ambient temperature and winter season are the risks for all stroke types,^[23]

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cerebral infarction (CI),^[18] or intracerebral hemorrhage (ICH).^[25] Many studies worldwide generally reported similar trends.^[5,6,9,15,28,29] On the other hand, maybe due to regional differences, some studies reported that spring is the risk for all stroke types^[18,26] and that transient ischemic attack (TIA) occurs more frequently in spring and autumn.^[12]

Furthermore, calendar factors are also related to stroke occurrence. Nakaguchi *et al.* reported that Japanese national holidays are related to ICH occurrence. They also reported that, during RokuYo (traditional Japanese day of the week), the relative risk of ICH is extremely low on the traditionally unlucky days of ButsuMetsu and TomoBiki.^[17] On the other hand, Wang *et al.* reported that the onset of all stroke types is more frequent on weekdays than on weekends.^[27] Kokubo *et al.* also reported TIA frequently occurs on Monday.^[12]

Furthermore, some studies focused on the chronological changes of the meteorological factors, because physical responses to environmental changes may be delayed. Short-term change of ambient temperature is related to stroke.^[7] Nonlacunar CI occurrence is related to atmospheric pressure (AP) falls, and ICH is associated with AP rises.^[10] Besides, 2–5 days after cold exposure^[6,28] or the increased or decreased AP 3 days before the onset from 4 days before^[24] are risks of CI. Furthermore, ICH frequently occurs after 4-day periods of mean AP in excess of 1015 hPa.^[16] In addition, ICH increases when the thermohydrological index (THI) gets extremely cooler in 4 days prior.^[14]

These studies suggested that meteorological conditions on the onset day as well as chronological changes in the former days may play important roles for the stroke occurrence. However, the prediction of the stroke occurrence is still difficult because the meteorological conditions and patients' backgrounds vary from region to region.

Recently, artificial intelligence (AI) is attracting. Especially, it is a transitional period regarding AI from machine learning to deep learning (DL). DL applications use a layered structure of algorithms called an artificial neural network (ANN). The design of ANN is inspired by the biological neural network of the human brain, leading to a process of learning that's far more capable than that of standard machine learning models.^[11] Gradually, DL is starting to be used as well in decision-making for spinal canal stenosis,^[1] predicting outcomes after stroke,^[2,11] pathological diagnosis,^[13] or radiomics studies of brain tumors.^[3] However, there are no reports on the prediction models for stroke occurrence using DL from the meteorological and calendar factors. DL can treat chronological data, sentences, and images that are difficult to be processed statistically. Therefore, we herein produced the prediction models for daily stroke occurrences using DL software, Prediction One (Sony Network Communications Inc., Tokyo, Japan) with chronologically meteorological and calendar data as well as our stroke dataset.

MATERIALS AND METHODS

Study population

We retrospectively investigated the daily stroke occurrence between January 2017 and December 2019 from the Kesennuma City Hospital's medical records. The occurrence date was defined as the time when the ambulance or patients arrived at our hospital. Stroke subtypes include CI, hypertensive ICH, and aneurysmal subarachnoid hemorrhage. CI includes cardioembolic infarction, atherothrombotic infarction, lacunar infarction, or others according to the Trial of Org 10172 in Acute Stroke Treatment (TOAST) criteria.^[19] TIA was also included. Hemorrhagic infarction and trauma-induced hemorrhage were excluded. Nonhypertensive hemorrhagic stroke due to tumor, arteriovenous malformation, moyamoya disease, and cerebral amyloid angiopathy was also excluded from the study. The diagnosis of stroke was based on clinical history and the findings on the computed tomography or magnetic resonance imaging. The hospital's research ethics committee approved this study, and we gained written informed consent for this study from all of the patients, the legally authorized representative of the patients, or next of kin of the deceased patients. All methods were carried out in accordance with relevant guidelines and regulations (Declaration of Helsinki).

Study area

Japan is located in a temperate climate zone with four distinct seasons: spring, summer, autumn, and winter. Miyagi prefecture, where Kesennuma City Hospital^[21] locates, is in the Northeastern part of Japan (north latitude 38.5° and east longitude 141.3°) in a Dfa zone (cold, without dry season, and hot summer), based on Köppen-Geiger climate classification [Figure 1a].^[20] Kesennuma City Hospital [red triangle in Figure 1b] is one of the three acute care hospitals which have the departments of neurosurgery in the Ishinomaki, Tome, and Kesennuma medical area with background populations of about 350,000 people [light green area in Figure 1b].

Meteorological data

Meteorological data in this study included daily mean ambient temperature (T_{mean}, °C), daily highest ambient temperature (T_{max}, ghes daily lowest ambient temperature (T_{min}, atu daily difference between the highest and lowest ambient temperature (T_{max}-min, °C), daily mean AP (Pa, hPa), daily mean vapor pressure (hPa), mean wind speed (m/s), daily amount of the rainfall (mm) or snowfall (mm), sunlight hours (h), and daily mean relative humidity (RH, %) of the 24 h calendar day period (0:00 AM–11:59 PM) on the onset day and the past 7 days, which were obtained from the local meteorological observatories (Japan Meteorological Agency, Ministry of Land, Infrastructure, Transport and

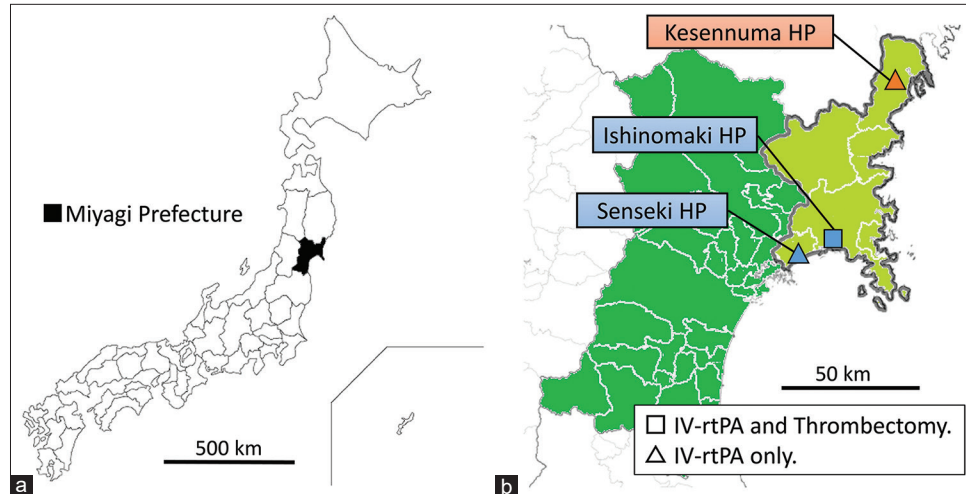


Figure 1: (a) Miyagi prefecture is located in the northeastern part of Japan. (b) Map of Miyagi prefecture. The Ishinomaki, Tome, and Kesennuma medical area, with background populations of about 350,000 people, is inside the thick line and colored with light green. The blue square is Japanese Red Cross Ishinomaki Hospital (HP), where both intravenous (IV) rt-PA and thrombectomy capable in this medical area. The blue triangle (Senseki HP) and the red triangle (Kesennuma City HP, where this study was performed) are IV rt-PA capable hospitals.

Tourism). The THI ($^{\circ}\text{C}$) was calculated using the formula; $\text{THI} = \text{Tmean} - 0.55 \times (1 - 0.01 \times \text{RH}) \times (\text{Tmean} - 14.5)$ as reported previously.^[24] This index is an established appropriate measure for the evaluation of the effect of air temperature on health outcomes because it takes into account mean air temperature after controlling for the effect of RH. The distance from our hospital to the local meteorological observatory was 3.8 km. All meteorological data were obtained from the website of each local meteorological observatory (Available from the Japan Meteorological Agency, Ministry of Land, Infrastructure, Transport and Tourism's Japan Meteorological Agency Official Homepage. <https://www.data.jma.go.jp/obd/stats/etrn/index.php>). The daily changes of some meteorological factors, including Tmean, Tmax, Tmin, Tmax-min, Pa, RH, and THI, for the past 7 days from the onset were calculated as follows; day-by-day difference, difference every 2 days, 3 days, 4 days, 5 days, and 6 days.

Calendrical variables

We also investigated the various calendrical variables over the study period, including date, day of the week, national holidays, and RokuYo. According to RokuYo, each day is classified as 1 of 6 days in a recurring 6-day calendrical series consisting of SenSho, TomoBiki, SenBu, ButsuMetsu, TaiAn, and ShakKo. ButsuMetsu is believed to be an unlucky day, when weddings and special events are avoided, and many crematories in Japan are closed on TomoBiki. Conversely, the other days of RokuYo, especially TaiAn, are believed to be lucky days, and events or ceremonies are generally scheduled for these days.

Making prediction model by Prediction One

We used Prediction One software to make the prediction models for daily stroke occurrence using 221 variables described above. Prediction One read the 3-year dataset and automatically divided them into almost a half as internal training and cross-validation datasets. Prediction One automatically adjusted and optimized the variables in a way that is easy to process statistically and mathematically, and select appropriate algorithm with ensemble learning. Prediction One made the best prediction model by ANN with internal cross-validation. The details are trade secrets and could not be provided.

We made three prediction models; one for all daily stroke occurrences (just present or absent), one for daily CI occurrences, and the other for daily ICH occurrences. Each model made by Prediction One exported predicted numbers of the daily stroke occurrences, each probability of the number of the daily occurrences from 0 to 4, and the expected values from the probabilities. We then use these values as predictive markers for the stroke, CI, or ICH occurrences binomially (present or not). The area under the curves (AUC) of the receiver operating characteristic curve (ROC) of each value was statistically calculated, and we evaluated the models' accuracy.

Statistical analysis

Results are shown as median (interquartile range). AUC of ROC was calculated using SPSS software version 24.0.0. (IBM, New York, USA). A two-tailed $P < 0.05$ was considered statistically significant.

RESULTS

Clinical characteristics

The monthly incidence of the 608 stroke patients (371 CI, 184 ICH, and 53 SAH) and monthly meteorological factors are summarized in [Table 1]. The median (interquartile range) age was 75 (66–81), and 254 women and 354 men were included.

Model development for all stroke, CI, and ICH occurrence

Prediction One produced each prediction model and value in <5 min. Against the stroke occurrence (present or not), the AUCs of predicted numbers of stroke occurrences, probability of each number of stroke patients as 0, 1, 2, 3, and 4, and the expected value were 0.693, 0.243, 0.717, 0.589, 0.532, 0.580, and 0.693, respectively [Figure 2]. Against the CI occurrence (present or not), the AUCs of predicted numbers of CI occurrence, probability of each number of CI patients from 0, 1, 2, to 3, and the expected value were 0.688, 0.218, 0.773, 0.609, 0.600, and 0.768, respectively [Figure 3]. Against the ICH occurrence (present or not), the AUCs of predicted numbers of ICH occurrences, probability of each number of ICH patients from 0, 1, 2, to 3, and the expected value were 0.988, 0.262, 0.737, 0.726, 0.714, and 0.731, respectively [Figure 4].

DISCUSSION

We made preliminarily prediction models of daily stroke, CI, and ICH occurrences (present or not) using DL software, Prediction One, with 221 meteorological and calendar variables. This is the first report on making DL-based prediction models for the daily stroke occurrence only from the meteorological and calendar variables.

The need for prediction of stroke occurrence

The previous studies on the association between meteorological or calendar data and stroke occurrence were statistically performed, and the meteorological or calendar risk factors for stroke occurrence were already revealed. However, accurate prediction of the stroke occurrence is still difficult, so stroke neurologists and comedicals must be on the alert at all times. In Japan, 7500 neurosurgeons work according to the 2018 statistics.^[30] In other words, there are about five neurosurgeons/100,000 people in Japan on average. Almost all of those in the acute care hospital work as general stroke neurologists at the normal outpatient, emergency room, operating room, stroke care unit, intensive care unit, and rehabilitation room. However, especially in the Ishinomaki, Tome, and Kesennuma medical area, which was shaken by an earthquake of magnitude 9.0 and hit by a subsequent tsunami on March 11, 2011,^[22] there are about two neurosurgeons/100,000 people. Kesennuma City Hospital is the only local hospital with a surgical suite for neurosurgical entities, and the two

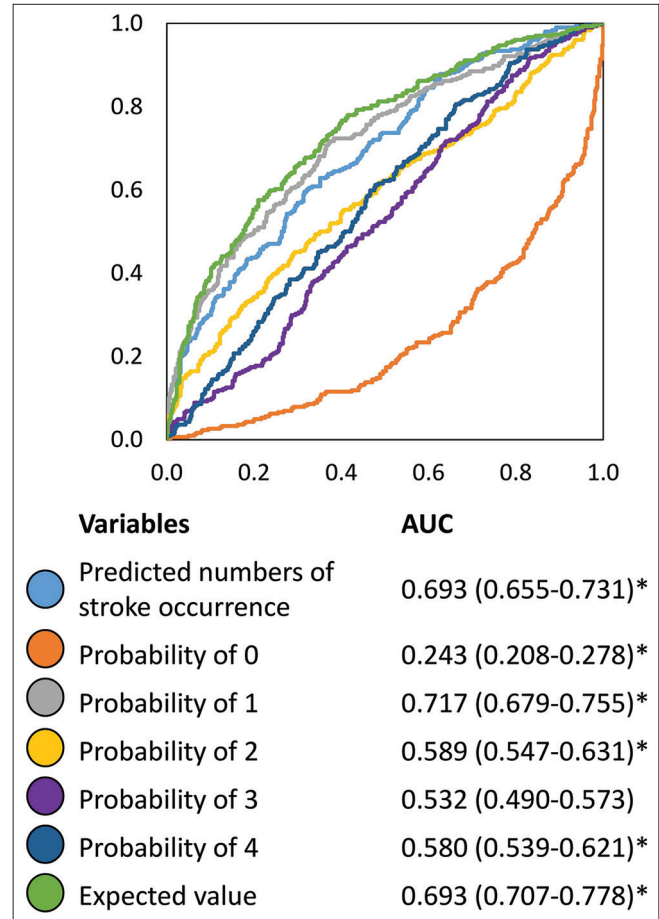


Figure 2: Against the stroke occurrence (present or not), the area under the curves of predicted numbers of stroke occurrences, probability of each number of stroke patients as 0, 1, 2, 3, and 4, and the expected value were 0.693, 0.243, 0.717, 0.589, 0.532, 0.580, and 0.693, respectively.

staff neurosurgeons not only perform surgery but also treat patients with neurologic diseases that are usually treated by neurologists, such as CI and epilepsy.^[21] Therefore, we cannot go out of Kesennuma city and are always on-call 24/7, and the stress is enormous. Therefore, we hypothesized that by predicting the stroke occurrence, our stress would be smaller. Furthermore, we do not have an intensive care unit in Kesennuma City Hospital, and comedicals work only in the general wards, so they would benefit from the prediction of the stroke occurrence, which makes their work more efficient. In addition, patients themselves may be able to self-care, such as drinking water and air conditioning, by knowing whether they are likely to have a stroke depending on the weather or calendar factors.

Future outlook

Simple DL software is being developed, so we should have an active interest in using it for the benefit of medical staff and

Table 1: Stroke incidence and meteorological factors.

Year	Month	Incidence (number)				Meteorological factors (monthly average)		
		All stroke	CI	ICH	SAH	Tmean (°C)	Pa (hPa)	RH (%)
2017	January	16	10	5	1	1.3	1009.5	64
	February	20	12	6	2	2.3	1007.8	62
	March	15	5	8	2	4.0	1009.6	64
	April	16	10	4	2	9.9	1007.9	66
	May	24	11	10	3	15.7	1008.0	70
	June	13	7	4	2	17.0	1004.4	79
	July	14	10	2	2	23.6	1004.4	82
	August	11	7	4	0	21.8	1004.8	89
	September	16	13	2	1	19.4	1007.5	79
	October	9	3	5	1	13.7	1014.7	80
	November	14	4	8	2	8.1	1012.3	68
	December	23	11	10	2	2.5	1010.3	66
Total of 2017		191	103	68	20	11.6	1008.4	72
2018	January	22	12	9	1	0.9	1008.2	61
	February	15	9	6	0	0.4	1011.5	60
	March	13	6	6	1	6.8	1012.5	60
	April	22	11	8	3	11.4	1009.6	66
	May	13	5	8	0	15.4	1007.0	71
	June	16	11	2	3	18.5	1005.3	81
	July	21	16	4	1	23.6	1006.7	87
	August	19	14	5	0	23.6	1005.1	83
	September	15	9	6	0	19.9	1010.1	84
	October	24	18	5	1	15.2	1011.7	77
	November	13	4	7	2	9.3	1015.7	71
	December	12	6	4	2	3.5	1013.2	66
Total of 2018		205	121	70	14	12.4	1009.7	72
2019	January	18	10	4	4	1.3	1010.2	61
	February	11	8	2	1	2.0	1012.9	61
	March	14	10	3	1	5.3	1008.3	63
	April	21	12	8	1	8.9	1008.7	66
	May	25	19	6	0	16	1004.0	67
	June	12	9	2	1	17.8	1006.2	83
	July	19	14	4	1	21.7	1004.9	83
	August	16	15	1	0	24.8	1011.5	83
	September	16	10	3	3	21.1	1013.1	78
	October	23	16	5	2	15.8	1013.1	80
	November	16	11	2	3	8.6	1013.6	66
	December	21	13	6	2	4.1	1014.4	68
Total of 2019		212	147	46	19	12.2	1010.1	72
Total of 3 years		608	371	184	53	12.4	1009.4	72

CI: Cerebral infarction, ICH: Intracerebral hemorrhage, Pa: Mean atmospheric pressure, RH: Mean relative humidity, SAH: Subarachnoid hemorrhage, Tmean: Mean ambient temperature

patients. Our study did not produce a good prediction model from the meteorological and calendar data and was just one example. However, we suggested the potential of DL software. DL-based efficient medicine, depending on each patient and hospital, would be performed as DL software becomes more popular. Nowadays, smartphone apps or smartwatches^[31] can, in real time, observe personal health records and daily physical activities outside of the hospital, and web-based observational studies have been performed. In the future, by synchronizing a wide variety of medical information,^[4,8] including medical

history, medications, genetic information, and radiomics, among the electronic medical records, personal smartphones, and smartwatches as well as integrating the physical activities or meteorological conditions in real time, the prediction of stroke occurrences could be performed with much higher accuracy. Our study is preliminary and the first step to this dreamlike medicine. We believe that, in the near future, we would see efficient medicine based on DL and synchronized huge personal health data, leading to the best use of limited medical resources, such as assigning doctors, nurses, to the

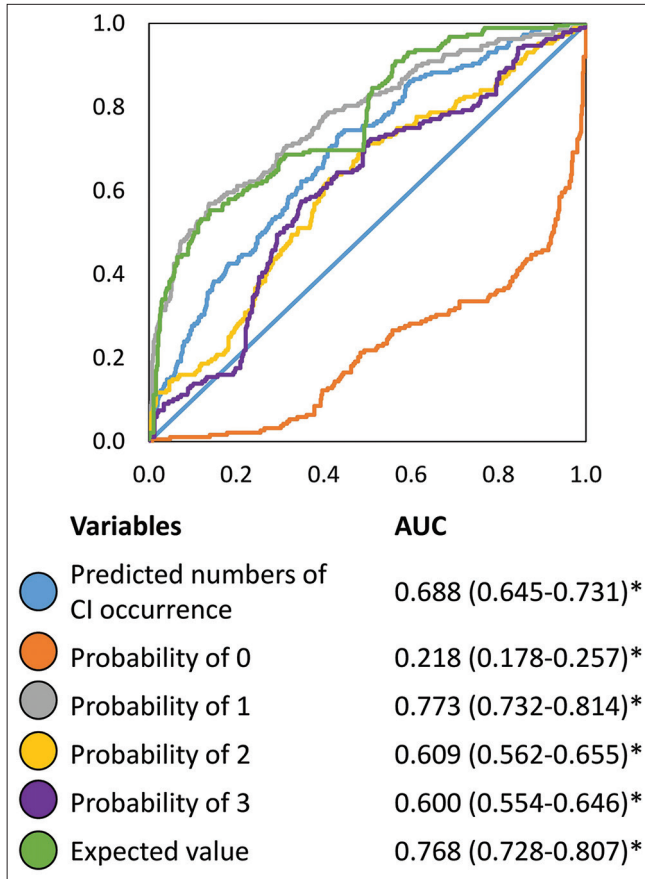


Figure 3: Against the cerebral infarction (CI) occurrence (present or not), the area under the curves of predicted numbers of CI occurrence, probability of each number of CI patients from 0, 1, 2, to 3, and the expected value were 0.688, 0.218, 0.773, 0.609, 0.600, and 0.768, respectively.

appropriate location, and time, based on the forecast of a stroke event.

Limitations of DL

We need to examine the clinical usefulness of the prediction models prospectively. For example, by predicting the stroke occurrence, we would evaluate the reduction of the workload and stress of the medical staff, and examine whether the medical resources and costs could be saved or not. Furthermore, we could examine the changes of the patients' activities after showing the result of DL-based stroke prediction, similar to carrying an umbrella or not according to the information from the weather forecasts.

We used Prediction One software, but there are many AI softwares (frameworks) worldwide, and there are a thousand different ways to assemble the ANN (libraries). Prediction One is suitable for predicting binomial, ordinal, or continuous variables and can treat Japanese sentences themselves. Furthermore, when there are missing values, it automatically

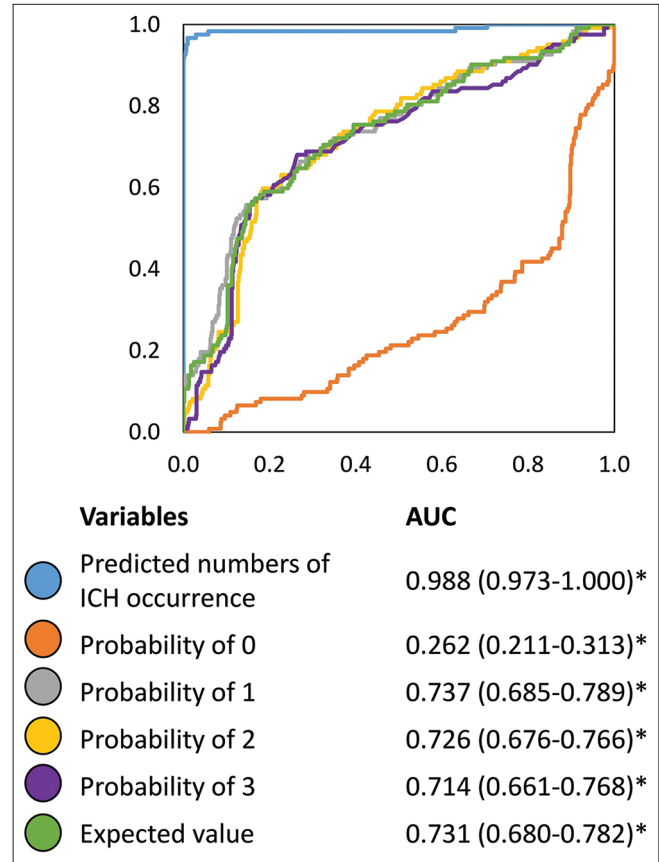


Figure 4: Against the intracerebral hemorrhage (ICH) occurrence (present or not), the area under the curves of predicted numbers of ICH occurrences, probability of each number of ICH patients from 0, 1, 2, to 3, and the expected value were 0.988, 0.262, 0.737, 0.726, 0.714, and 0.731, respectively.

compensates. However, the details of how the ANN is assembled and tuned have not been released, so we need to think carefully about the accuracy of the models. Furthermore, Prediction One suggested important variables like “the difference of Tmax between day 5 and day 2,” but we should investigate why the variables were judged as important, considering the clinical meaning. Furthermore, we tried to predict the “numbers” of stroke occurrences, and the F-values of the models, which are an indicator of the AI-based model accuracy, were ranging from 0.745 to 0.912. They seemed good, but the predicted values were all 0. This is because the actual predicted numbers of the patients were ranging from 0.061 to 0.689, and the cutoff value was above those. In other words, DL, in this study, could not predict the actual numbers of strokes. Therefore, we separately calculate the AUCs using each exported values in this study.

Limitation of this study

First, we used the data from only 3 years, so further studies using that from the previous years or various regions should

be performed. Second, some of the patients lived alone and were found by someone sometime after the stroke onset, and others of them came to our hospital a few days after conservation by themselves, so the models actually predicted the number of “visits” to the hospital, but not the occurrences. Third, the meteorological data are based on the 24 h calendar day period (0:00 AM–11:59 PM), but the work at the hospital begins at approximately 9:00 AM, and it should be the start line. Due to these reasons, the accurate hourly prediction would be further difficult compared to the daily one. Fourth, we should try to perform external validation.

CONCLUSION

We preliminarily made prediction models of daily stroke, CI, and ICH occurrences (present or not) using DL software, Prediction One, with meteorological and calendar variables. This is the first report on making DL-based prediction models for the daily stroke occurrences only from the meteorological and calendar variables. In the future, by synchronizing a wide variety of medical information among the electronic medical records, personal smartphones, and smartwatches as well as integrating the physical activities or meteorological conditions in real time, the prediction of stroke occurrence could be performed with much higher accuracy, to save the medical resources, to have patients care for themselves, and to perform efficient medicine.

Declaration of patient consent

The authors certify that they have obtained all appropriate patient consent.

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Nil.

Conflicts of interest

There are no conflicts of interest.

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