Usefulness of an artificial neural network for a beginner to achieve similar interpretations to an expert when examining myocardial perfusion images

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Abstract
This study examined whether using an artificial neural network (ANN) helps beginners in diagnostic cardiac imaging to achieve similar results to experts when interpreting stress myocardial perfusion imaging (MPI). One hundred and thirty-eight patients underwent stress MPI with Tc-labeled agents. An expert and a beginner interpreted stress/rest MPI with or without the ANN and the results were compared. The myocardium was divided into 5 regions (the apex; septum; anterior; lateral, and inferior regions), and the defect score of myocardial blood flow was evaluated from 0 to 4, and SSS, SRS, and SDS were calculated. The ANN effect, defined as the difference in each of these scores between with and without the ANN, was calculated to investigate the influence of ANN on the interpreters’ performance. We classified 2 groups (insignificant perfusion group and significant perfusion group) and compared them. In the same way, classified 2 groups (insignificant ischemia group and significant ischemia group) and compared them. Besides, we classified 2 groups (normal vessels group and multi-vessels group) and compared them. The ANN effect was smaller for the expert than for the beginner. Besides, the ANN effect for insignificant perfusion group, insignificant ischemia group and multi-vessels group were smaller for the expert than for the beginner. On the other hand, the ANN effect for significant perfusion group, significant ischemia group and normal vessels group were no significant. When interpreting MPI, beginners may achieve similar results to experts by using an ANN. Thus, interpreting MPI with ANN may be useful for beginners. Furthermore, when beginners interpret insignificant perfusion group, insignificant ischemia group and multi-vessel group, beginners may achieve similar results to experts by using an ANN.

Keywords Artificial neural network · Myocardial perfusion images · Artificial intelligence · Nuclear medicine · Cardiology imaging

Abbreviations
MPI Myocardial perfusion imaging
AI Artificial intelligence
ANN Artificial neural network
SSS Summed stress score
SRS Summed rest score
SDS Summed difference score
ML Machine learning

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Introduction

During the last 20 years, artificial intelligence (AI) and machine learning (ML), including artificial neural networks (ANN), have markedly developed. AI and ML may aid medical imaging-based diagnosis, not only in terms of the detection of disease, but also in management, reporting, and prognostication [1]. ANN is a computational model of ML based on the human brain. It has been found that ANN are powerful tools for pattern recognition, signal processing, image or speech data compression, and learning expert systems [2]. There are 6675 radiologists with specialty licenses in Japan, according to the Japan Radiological Society, but only 1317 radiologists have specialty licenses in nuclear medicine. In particular, the number of experts in cardiac nuclear medicine is very small. The interpretation of myocardial perfusion images (MPI) requires skilled expert reading, but there are not as many skilled experts in the interpretation of MPI as there are in the interpretation of computed tomography scans in Japan.

Recently, many studies have shown that AI and ML significantly improve the diagnostic accuracy not only in cardiology, but also in many other medical fields [3, 4]. However, there has not been sufficient research on the use of AI in cardiac nuclear medicine. Nuclear medicine imaging techniques, such as MPI, do not provide as much data as other imaging techniques; therefore, AI may be useful for inexperienced physicians working in radiology or cardiology when they interpret MPI. If the use of AI helps beginners to achieve similar interpretations to experts when examining MPI, it would help to compensate for a lack of human resources.

The purpose of this study was to examine whether a beginner in diagnostic cardiac imaging can achieve similar results to an expert when interpreting stress MPI by using an ANN.

Methods

Subjects

The subjects were 138 consecutive patients who underwent stress MPI (with Tc-labeled agents) at Nagasaki University Hospital between May 2014 and June 2015, including 52 patients (38%) with multivessel disease, 35 patients (25%) with a history of myocardial infarction, and 21 patients (15%) with both multivessel disease (MVD) and a history of myocardial infarction. MVD is defined as 2 and more coronary arteries with 75% and more stenosis evaluated by CT angiography (CTA) and/or coronary angiography (CAG). Of these 138 patients, 8 patients (6%) underwent only CTA, 61 patients (44%) underwent only CAG, and 26 patients (19%) underwent both CTA and CAG. Of 52 patients with MVD, 1 patient (2%) underwent CTA, 32 patients (62%) underwent CAG, and 19 patients (37%) underwent both CTA and CAG. An expert with over 20 years’ interpretation experience and a beginner with a few years’ interpretation experience interpreted stress MPI with/without software, which implemented ANN, and the results were compared. They interpreted randomly these MPI without any information except patients’ age and sex. The patients’ characteristics are shown in Table 1.

Imaging

The stress and rest MPI studies were performed using a 1-day stress-first protocol and about 1200 MBq of a 99mTc-labeled myocardial perfusion agent (tetrofosmin or MIBI; divided into 300 MBq for the stress imaging and 900 MBq for the rest imaging). The indications and stress protocols followed the guidelines of the Japanese Circulation Society [5]. An adenosine stress test was performed with a standard continuous injection protocol, involving an injection rate of

| Table 1 | Demographics of patients that underwent stress myocardial perfusion imaging |
|---------|-----------------------------------------------------------------------------|
| n = 138 | Mean ± SD (range), n (%)                                                     |
| Age (years) | 70.6 ± 0.8 (36–87)                                                        |
| Sex (male)  | 94 (68.1%)                                                                  |
| Height, weight (male) | 164 ± 0.7 cm, 61.3 ± 1.2 kg                        |
| Body mass index (male) | 22.7 ± 0.4 kg/cm²                                                        |
| Height, weight (female) | 149.7 ± 1.0 cm, 48.8 ± 1.5 kg                   |
| Body mass index (female) | 21.8 ± 0.6 kg/cm²                                                        |
| No. of vessels displaying  | 63:23:17:35 (MVD: 38%)                                               |
| ≥ 75% stenosis (0, 1, 2, 3) | 63:23:17:35 (MVD: 38%)                                               |
| Hypertension | 94 (68.1%)                                                                  |
| Diabetes mellitus | 53 (38.4%)                                                                  |
| Dyslipidemia | 93 (67.4%)                                                                  |
| History of MI | 35 (25.3%)                                                                  |
| History of PCI/CABG | 53 (38.4%), 18 (13%)                                                        |
| Only CTA | 8 (6%)                                                                      |
| Only CAG | 61 (44%)                                                                    |
| Both CTA and CAG | 26 (19%)                                                                   |
| LVEF (%) (QGS, stress) | 67.4 ± 1.4                                                                 |
| LVEF (%) (QGS, rest) | 68.7 ± 1.0                                                                 |
| LVEDV (ml) (QGS, stress) | 31.8 ± 3.3                                                                |
| LVEDV (ml) (QGS, rest) | 32.5 ± 2.2                                                                 |

CABG coronary artery bypass grafting, MI myocardial infarction, MVD multivessel disease, PCI percutaneous coronary intervention, LVEF left ventricle ejection fraction, LVEDV left ventricle end-diastolic volume, QGS quantitative gated SPECT, CTA CT angiography, CAG coronary angiography
0.12 mg·kg⁻¹·min⁻¹, in 136 patients (98.6%), and an exercise stress test, involving symptom-limited ergometer exercise, was conducted in 2 patients (1.4%). The end-points of the exercise stress test included significant symptoms (such as chest pain, dyspnea, or leg fatigue), the achievement of the target heart rate, electrocardiographic changes (ST depression, ST elevation, fatal arrhythmia, or blood pressure problems [very high pressure of > 250 mmHg or hypotension]). One hour after the injection of the tracer, the patients were imaged using a dual-headed single-photon emission computed tomography (SPECT) system, equipped with low-energy high-resolution collimators (e.cam Signature; Siemens Healthcare GmbH, Germany); a 180° arc; and a 16 frames/beat acquisition protocol. The acquisition energy level was set at 140 keV with a 20% window fitted for ⁹⁹mTc. All of the patients were instructed to refrain from eating food (breakfast) before the scans.

**Image interpretation and scoring**

The images were interpreted and scored in a medical image viewer, using the hospital’s Picture Archiving And Communication System (PACS) (Synapse; Fujifilm, Tokyo, Japan) with or without the diagnostic ANN software, (cardioREPO, version 1.1; Fujifilm Toyama Chemical, Tokyo, Japan). This software analyzes MPI via a ML system, which was trained using about 1000 patients’ images, and displays areas of abnormal stress perfusion and ischemic areas on a polarmap. The details of the method are described in Fig. 1 [6, 7]. Briefly, ANN software is trained with about 1000 patients’ stress polarmap and subtraction polarmap of stress and rest. When the users loaded stress and rest short axis images of each patient, the software automatically creates polarmaps of stress, rest and subtraction of stress and rest. Then calculate ANN value which is a probability of abnormal myocardium on stress polarmap which correspond to both infarction and ischemia. The program also draws white lines on the polarmap, indicating abnormal areas detected on subtraction polarmap which mainly correspond to ischemia. However, the interpretation of ischemia on this program is different from that with human interpretation, abnormal area indicated on black line and white line does note match with human interpretation always (for example, with human interpretation, ischemia is always included in the abnormal area on stress images because human interpret ischemia as abnormal on stress but normal on rest. However, ischemia on program is sometimes locates outside of stress abnormal area because ischemia is detected on the subtraction polarmap, not with the comparison of stress and rest polarmap).

Usually, a 17-segment model is used for myocardial perfusion scoring [8]. However, our study aimed to examine the effects of AI on the performance of beginners during image interpretation. To simplify the scoring for the beginner, the myocardium was divided into 5 regions; i.e., the apex; septum; and the anterior, lateral, and inferior regions [9]. The degree of abnormal perfusion distribution defined as defect score was classified from 0 to 4 (0; normal perfusion, 1; mild drop in perfusion, 2; moderate drop in perfusion, 3; severe drop in perfusion, 4; defect of perfusion). The sum total of these 5 regions measured on stress image was defined as summed stress score (SSS), that measured on rest image was defined as summed rest score (SRS), and the difference between SSS and SRS (SSS – SRS) was defined as summed difference score (SDS). Thus, high SSS and high SRS (= low SDS) corresponds to myocardial infarction, high SSS and low SRS (= high SDS) corresponds to myocardial ischemia and low SSS and low SRS (= low SDS) corresponds to normal myocardium. Max SSS in this study is 20 in our 5 regions model on the count. These parameters were obtained without help of the ANN once. Then after several weeks interval to ensure that previous interpretation would fade from the memory of interpreters, score parameters were

![Fig. 1](https://example.com/fig1.png)  
**Fig. 1** ANN analysis of stress MPI by cardioREPO. The region within the black line: the region exhibiting abnormal perfusion. The region within the white line: the ischemic region. The region within the black line, but not within the white line: a myocardial infarction [6]
again obtained with help of ANN display (Fig. 1) side by side to original image. Using this ANN polarmap display as additional information, both interpreters scored each image individually. Namely a beginner and an expert interpreted individually myocardial SPECT images and scored SSS, SRS, and SDS with only information of these patients’ sex and age without ANN. Polarmaps are like answers of these images, so they interpreted each segments model (horizontal long axis view, short axis view, vertical long axis view) without Polarmaps. To avoid influence on previous interpreting, after several day interval, they interpreted individually myocardial SPECT images with same manner but with help of ANN display. In order to investigate the influence of the ANN on the interpreters’ performance, the ANN effect was calculated as the difference in each score (SSS, SRS, or SDS) between with and without the ANN for both the beginner and expert. A larger ANN effect indicates that the findings were interpreted more accurately with than without the ANN.

We classified severity of abnormal perfusion into four categories (normal, mild, moderate and severe) with following manners. We classified SSS and SDS into four categories using classification used by Czaja et al. Czaia used 17 segment model and we used 5 segment model. Thus the number threshold used for the classification was converted according to this difference of segment number resulting SSS/SDS = 0 was classified as normal (or minimally abnormal), SSS/SDS = 1 was classified as minimally abnormal, SSS/SDS = 2 was classified as moderately abnormal and SSS/SDS = 3 or more was classified as significantly abnormal [10]. Patient with %ischemia exceeding 10% are believed to benefit from revascularization regardless of their left ventricular ejection fraction [11]. Thus in our analysis, SDS = 2 or more corresponds to %ischemia over 10%. We show Table 2 for help.

Statistics

All data are expressed as mean ± standard deviation (SD) values. The significance of differences was examined by one-way analysis of variance with the F test or paired t-test. P-values of < 0.05 were considered to be significant. All statistical analyses were performed using the JMP 10.0.2 software.

All procedures performed in studies involving human participants were in accordance with the ethical standards of the institutional research committee and with the 1964 Declaration of Helsinki and its later amendments. All clinical data were completely anonymized and processed at Nagasaki University Hospital. This study was approved by Nagasaki University Hospital Clinical Research ethics committee (Approval No. 15072762).

Results

Interpretation of images

The results are shown in Table 3. The ANN effect for all 138 patients was smaller for the expert than for the beginner (SSS: −0.49 vs. −1.23, p < 0.0001; SRS: −0.34 vs. −0.88, p = 0.0003; SDS: −0.15 vs. −0.36, p = 0.0128, respectively). The ANN effects for all 138 patients on SSS, SRS, and SDS were negative for both interpreters, which indicates that they had lower scores with than without the ANN; i.e. their diagnostic approach became more conservative when they were using the ANN. The absolute ANN effect value was lower in the expert than in the beginner, which means that the

Table 2 Citation and alteration from [10] (when max SSS = 20)

| SSS | SS%  | SDS | Result             |
|-----|------|-----|--------------------|
| 0   | <5   | 0   | Normal or minimally abnormal |
| 1   | 5–9  | 1   | Mildly abnormal    |
| 2   | 10–14| 2   | Moderately abnormal |
| 3+  | >14  | 3+  | Significantly abnormal |

Table 3 Results

|        | Expert       | Beginner     | p-value |
|--------|--------------|--------------|---------|
| SSS    | −0.49 ± 0.08 | −1.23 ± 0.15 | <0.0001 |
| SRS    | −0.34 ± 0.07 | −0.88 ± 0.13 | 0.0003  |
| SDS    | −0.15 ± 0.06 | −0.36 ± 0.08 | 0.0128  |

ANN artificial neural network, SSS summed stress score, SRS summed rest score, SDS summed difference score
The ANN effect for 78 patients (insignificant perfusion group, SSS = 0 and 1) was smaller for the expert than for the beginner (SSS: −0.27 vs. −1.28, p < 0.0001; SRS: −0.09 vs. −0.88, p < 0.0001; SDS: −0.18 vs. −0.40, p = 0.0185, respectively). The ANN effect for 116 patients (insignificant ischemia group, SDS = 0 and 1) was smaller for the expert than for the beginner (SSS: −0.30 vs. −1.28, p < 0.0001; SRS: −0.09 vs. −0.88, p < 0.0001; SDS: −0.12 vs. −0.30, p = 0.0003, respectively).

The ANN effect for 60 patients (significant perfusion group, SSS = 2 and more) was no significant between the expert and the beginner (SSS: −0.78 vs. −1.17, p = 0.2060; SRS: −0.67 vs. −0.87, p = 0.4631; SDS: −0.12 vs. −0.30, p = 0.2067, respectively).

The more detailed results are shown in Table 4. The ANN effect for 78 patients (insignificant perfusion group, SSS = 0 and 1) was no significant for the expert then for the beginner (SSS: −0.27 vs. −1.28, p < 0.0001; SRS: −0.09 vs. −0.88, p < 0.0001; SDS: −0.18 vs. −0.40, p = 0.0185, respectively). The ANN effect for 116 patients (insignificant ischemia group, SDS = 0 and 1) was smaller for the expert than for the beginner (SSS: −0.30 vs. −0.97, p < 0.0001; SDS:0 vs. −0.30, p = 0.0003, respectively).

The ANN effect for 22 patients (significant ischemia, SDS = 2 and more) was no significant between the expert and the beginner (SSS: −1.50 vs. −1.01, p = 0.3732; SRS: −0.55 vs. −0.36, p = 0.7218; SDS: −0.95 vs. −0.64, p = 0.2162, respectively).

### Table 4 Precise results

| ANN effect                         | Expert       | Beginner    | p-value       |
|-----------------------------------|--------------|-------------|---------------|
| Insignificant perfusion group     |              |             |               |
| SSS                               | −0.27±0.55   | −1.28±1.39  | <0.0001       |
| SRS                               | −0.09±0.43   | −0.88±1.28  | <0.0001       |
| SDS                               | −0.18±0.50   | −0.40±0.80  | 0.0185        |
| Significant perfusion group       |              |             |               |
| SSS                               | −0.78±1.19   | −1.17±2.09  | 0.2060        |
| SRS                               | −0.67±1.02   | −0.87±1.93  | 0.4631        |
| SDS                               | −0.12±0.98   | −0.30±1.08  | 0.2067        |
| Insignificant ischemia group      |              |             |               |
| SSS                               | −0.30±0.77   | −1.28±1.66  | <0.0001       |
| SRS                               | −0.30±0.78   | −0.97±1.55  | <0.0001       |
| SDS                               | 0±0.62       | −0.30±0.87  | 0.0003        |
| Significant ischemia group        |              |             |               |
| SSS                               | −1.50±1.01   | −1.00±2.05  | 0.3732        |
| SRS                               | −0.55±0.86   | −0.36±1.71  | 0.7218        |
| SDS                               | −0.95±0.84   | −0.64±1.18  | 0.2162        |
| Normal vessels group (no coronary artery with 75% and more stenosis) | | | |
| SSS                               | −0.49±0.69   | −0.95±1.75  | 0.0623        |
| SRS                               | −0.29±0.68   | −0.73±1.52  | 0.0390        |
| SDS                               | −0.21±0.63   | −0.22±0.83  | 0.8802        |
| Multi-vessels group (2 and more coronary arteries with 75% and more stenosis) | | | |
| SSS                               | −0.49±1.08   | −1.47±1.67  | <0.0001       |
| SRS                               | −0.39±0.88   | −1.00±1.64  | 0.0031        |
| SDS                               | −0.11±0.83   | −0.47±0.99  | 0.0028        |

ANN artificial neural network, SSS summed stress score, SRS summed rest score, SDS summed difference score, MVD multi-vessel disease
We did not compare the image interpretation using ANN with other method such as coronary stenosis etc. As described in previous study by Nakajima et al. the aim of this study is whether this software can help to be close to expert interpretation, not be close to detect true ischemia. As noted on the method, ANN was trained with expert reading and not including detailed clinical information such as FFR, coronary flow reserve, myocardial perfusion etc. Thus theoretically, the ANN can be close to but cannot exceed expert.

We used an ANN to aid image analysis/interpretation. Arsanjani et al. showed that the LogitBoost method, which is another type of ML, exhibited almost the same accuracy when interpreting MPI as expert readers [14]. Our findings are similar.

Limitations

This study involved an expert and a beginner in cardiac nuclear medicine and was performed at Nagasaki University. Although we should have included a few experts and a few beginners to obtain sufficient data, there was only one expert in cardiac nuclear medicine in Nagasaki Prefecture.

In addition, we used a simplified 5-segment model instead of the conventional 17-segment model for scoring. This narrowed the range of scores (for 5 segments, the maximum value is 20, whereas for 17 segments the maximum value is 68), which may have reduced the statistical power of the study. However, a previous study, which analyzed a neural network support system, also used a 5-segment model. Thus, we consider that this 5-segment model did not markedly affect our results [9].

Strictly speaking, we should compare our study results with gold standard, but our study target is to achieve going beginners’ interpretation with AI up to human experts’ that. So we didn’t do it in this study [7].

Conclusions

When using an ANN, when interpreting MPI of insignificant perfusion group and insignificant ischemia group, beginners may achieve similar imaging interpretations to experts in cardiac nuclear medicine. Furthermore, ANN systems may be useful for obtaining a second opinion, particularly when physicians are inexperienced at interpreting nuclear cardiology imaging.

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Author contributions Nothing.

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Data availability The datasets generated during and/or analyzed during the current study are available from the corresponding author on reasonable request.

Declarations

Conflict of interest All authors declare that they have no conflict of interest.

Ethical approval All procedures performed in studies involving human participants were in accordance with the ethical standards of the institutional research committee and with the 1964 Declaration of Helsinki and its later amendments. All clinical data were completely anonymized and processed at Nagasaki University Hospital

Consent to participate This study was approved by Nagasaki University Hospital Clinical Research ethics committee (approval No. 15072762).

Informed consent Since this is a non-invasive retrospective study using only existing information, we conducted an opt out.

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