A Deep Learning Approach for Assessment of Regional Wall Motion Abnormality from Echocardiographic Images

Brief title: Deep Learning for Echocardiography

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Structured ABSTRACT

Objectives: The aim of this study was to evaluate whether a deep convolutional neural network (DCNN) could detect regional wall motion abnormalities (RWMAs) and differentiate groups of coronary infarction territories from conventional 2-dimensional echocardiographic images compared with cardiologist/sonographer or resident readers.

Background: An effective intervention for reduction of misreading of RWMAs is needed. We hypothesized that a DCNN trained with echocardiographic images may provide improved detection of RWMAs in the clinical setting.

Methods: A total of 300 patients with history of myocardial infarction were enrolled. In this cohort, 100 each had infarctions of the left anterior descending branch (LAD), left circumflex branch (LCX), and right coronary artery (RCA). The age-matched 100 control patients with normal wall motion were selected from our database. Each case contained cardiac ultrasound images from short axis views at end-diastolic, mid-systolic and end-systolic phases. After 100 steps of training, diagnostic accuracies were calculated on the test set. We independently trained 10 versions of the same model, and performed ensemble predictions with them.

Results: For detection of the presence of wall motion abnormality, the area under the receiver-operating characteristic curve (AUC) by deep learning algorithm was similar to that by cardiologist/sonographer readers (0.99 vs. 0.98, $p = 0.15$), and significantly higher than the AUC by resident readers (0.99 vs. 0.90, $p = 0.002$). For detection of territories of wall motion abnormality, the AUC by the deep learning algorithm was similar to the AUC by cardiologist/sonographer readers (0.97 vs. 0.95, $p = 0.61$) and significantly higher than the AUC by resident readers (0.97 vs. 0.83, p =0.003). In a validation group from an independent site (n=40), the AUC by the DL algorithm was 0.90.

Conclusions: Our results support the possibility of DCNN use for automated diagnosis of RWMAs in the field of echocardiography.

Key Words: echocardiography; artificial intelligence: regional wall motion abnormality; diagnostic ability

Condensed ABSTRACT

The aim of this study was to evaluate whether a deep convolutional neural network (DCNN) could detect regional wall motion abnormalities and differentiate groups of coronary infarction territories from conventional 2-dimensional echocardiographic images compared with expert and inexperienced readers. To detect the presence and territories of wall motion abnormality, the area under the receiver-operating characteristic curve by deep learning algorithm was similar to that by cardiologist/sonographer readers and significantly higher than the area under the curve by resident readers. These results demonstrate that DCNN can be trained to identify wall motion abnormality on echocardiographic images.

Abbreviations and Acronyms:

RWMAs = regional wall motion abnormalities, DCNN = deep convolutional neural network, LAD = left anterior descending branch disease, LCX = left circumflex branch disease, RCA = right coronary artery disease.

Two-dimensional echocardiography is currently the most widely used noninvasive imaging modality for evaluating regional wall motion abnormalities (RWMAs) in patients with coronary artery disease. Assessment of RWMAs is a Class I recommendation by the American College of Cardiology/American Heart Association and the European Heart Association by trained echocardiogram technicians in patients with chest pain in the emergency department (1,2). Identification of patients with RWMAs is useful to detect a significant occult coronary artery disease not evident by symptoms, electrocardiogram, or initial cardiac biomarkers. However, conventional assessment of RWMAs, which is based on visual interpretation of endocardial excursion and myocardial thickening, is subjective and experience-dependent (3). An effective intervention for reduction of misreading of RWMAs is needed (4-6).

Machine learning helps computers to learn and develop rules without requiring human instruction at all stages. Recently, deep learning (DL) has become a powerful method for detection and classification of several diseases in many medical fields (7-12). It may be a useful artificial intelligence tool for the assessment of cardiovascular disease (13-16). Conventional machine learning usually requires predefined measurements to characterize the information in the input image (17). In contrast, deep learning directly calculates the results beyond the predefining process (7,18). In addition, the deep layer of the convolutional neural network is able to extract detailed low-level information from the original image and may be useful to detect echocardiographic problems (19,20). We hypothesized that a deep convolutional neural network (DCNN) trained with echocardiographic images may provide improved detection of the RWMAs in the clinical setting. Our aim of this study was to demonstrate that a DCNN can automatically differentiate groups of coronary infarction territories from conventional 2-dimensional echocardiographic images compared with inexperienced and expert readers.

Methods

Study population. We retrospectively enrolled 400 patients who had undergone coronary angiography to evaluate coronary artery disease. In this cohort, 300 patients had prior myocardial infarctions. In brief, 100 patients had an anterior infarction (isolated left anterior descending branch disease: LAD), 100 had an infero-lateral infarction (isolated left circumflex branch disease: LCX) and 100 had an inferior infarction (isolated right coronary artery disease: RCA). The age-matched control group comprised 100 patients without obstructive coronary artery disease. None of the patients had atrial fibrillation or severe valvular disease. We have selected images with good or adequate acoustic detail on the basis of visualization of the LV walls and endocardium in order to test deep learning algorithm on echocardiographic images. To overcome the issue for the generalizability, we have gathered a separate validation group of 40 patients who were referred for coronary angiography from an independent site (Hoetsu Hospital in Tokushima, Japan). In this cohort, there were 10 patients with LAD asynergy, 5 patients with LCX asynergy, 9 patients with RCA asynergy, and 16 patients without asynergy. The Institutional Review Board of the Tokushima University Hospital approved the study protocol (no. 3217).

Echocardiography. Echocardiography was performed using a commercially available ultrasound machine (Vivid E9/E95; and GE Healthcare, Waukesha, WI). All echocardiographic measurements were obtained according to American Society of Echocardiography recommendations (21). All images were stored digitally for playback and analysis. Visual RWMAs were interpreted using short axis views by 10 cardiologist/sonographer and 10 resident observers’ consensus (22). Three territories (LAD, LCX, and RCA) were evaluated in the coronary angiography with combined wall motion evaluation using apical and short axis views.

We used consensus expert agreement of RWMA on the echo images as a gold standard, with the experts (K.K and H.Y. with >10 years' experience with echocardiography) able to take into account additional information available from angiography and ventriculography. These classifications were blinded from the results of the other analysis. The short-axis view which results in a circular view of the LV can be used at the middle level. The LAD feeds segments of anterior septum and anterior free wall, the RCA feeds segments of infero-septum and inferior free wall, and the LCX feeds segments of infero-lateral and lateral wall.

Import data. The import data process is shown in **Figure 1**. Each case contains cardiac ultrasound images from mid-level short axis views. To adjust for differences between patients in frame rate and heart rate, we used images at end-diastolic, mid-systolic and end-systolic phases. We transformed all DICOM images into 128x128 resolution portable network graphics images with down sampling. Three territories of data, as well as the control group data, were divided into a training set and a test set (80:20), so that total 400 cases with 1200 images were split with 256 cases (786 images) as the training set, 64 cases (192 images) as the validation set, and 80 cases (240 images) as the test set. We performed two steps of analysis; protocol 1: to detect the presence of RWMAs, and protocol 2: to detect the territory of RWMAs.

Deep learning model. The overall process is shown in **Central Illustration**. Detection of the presence of RWMAs and the territory of RWMAs was accomplished by a DCNN. We used ResNet, DenseNet, Inception-ResNet, Inception, and Xception for a DCNN (23-25). In order for the DCNN model to return the answer, one fully connected layer with 50% dropout was added to the model. DCNN trained from images assessed by expert cardiologists was used to estimate the probability of RWMAs in the LAD, LCX and RCA territories. The maximum probability was used as the probability of patient disease. The fully connected layers transform the image features into the final LAD, LCX, and RCA scores, by adjusting weights for neuron activations during training. Model training was performed on a graphics processing unit (GeForce GTX 1080 Ti, NVIDIA, Santa Clara, California, USA). Once the network is trained, it will calculate how far the trained model's output is from the actual output. Then, the cross-entropy function will try to reduce this error to a minimum point (26). Adam optimizer was used for training. After 100 steps of training, diagnostic accuracies were calculated on the test set. We independently trained 10 versions of the same DCNN model, and performed the voting scheme of ensemble prediction with them on the test set. We used the majority voting ensemble prediction to score the probability of RWMAs. The majority voting ensemble is one of representative ensemble methods that can combine the outputs of 10 trained different classifiers. These models were trained with the same initialization and learning rate policies. DL was performed with python 3.5 programming language with Keras 2.1.5. We have uploaded the code in GitHub and provided the link. GitHub: https://github.com/taka4abe/JACC_CV.

Statistical analysis. Data are presented as mean ± SD. Differences between multiple groups were analyzed by ANOVA followed by Tukey's post hoc analysis. The diagnostic performance of the DL algorithm and observers was evaluated using receiver operating characteristic (ROC) analysis and pairwise comparisons of the area under the ROC curve (AUC) according to the DeLong method (27). Statistical analysis was performed using standard statistical software packages (SPSS software 21.0; SPSS Inc, Chicago, IL, USA, and MedCalc Software 17; Mariakerke, Belgium). Statistical significance was defined by $p < 0.05$.

Results

The subject characteristics included in this study are shown in **Table 1**. The study population consisted of 300 patients with coronary artery disease (CAD) and 100 patients without CAD. LV ejection fraction was significantly lower in the LAD group than in the other groups. Wall motion score index was also higher in the LAD group than in the other groups. **Figure 2** shows the value of the loss function on the training and validation sets for training a DCNN model. As shown in this figure, the model converges in the training process near the100th epoch, and the data distributions were narrow range.

Detection for RWMAs. For detection of the presence of wall motion abnormality (wall motion abnormality vs. control), the AUC by the DL algorithm (ResNet) was similar to that by cardiologist/sonographer readers (0.99 vs. 0.98, $p = 0.15$), and significantly higher than the AUC by resident readers (0.99 vs. 0.90, $p = 0.002$).

Results of the ROC analysis used to assess the diagnostic ability for detecting the territories of RWMAs are shown in **Figure 3**. We have compared the AUCs by several DL algorithms for detection of territories of wall motion abnormality (LAD vs. LCX vs. RCA vs. control). The DL with largest AUC was ResNet (AUC: 0.97), but there was no significant difference among DL algorithms except for the Xception model (ResNet: AUC: 0.97, DenseNet: AUC: 0.95, Inception-ResNet: AUC: 0.89, Inception: AUC: 0.90, and Xception: AUC: 0.85, vs. other algorithms, $p < 0.05$). For detection of territories of wall motion abnormality, the AUC by the DL algorithm (ResNet) was similar to the AUC by cardiologist/sonographer readers (0.97 vs. 0.95, $p = 0.61$) and significantly higher than the AUC by resident readers (0.97 vs. 0.83, $p = 0.003$) (**Supplement 1**). To assess the diagnostic performance in each are separately, we have added the ROCs in **Supplement 2**. All AUCs were good.

To check the accuracy of RWMA identification for each coronary territory, we calculated the odds ratio of DL vs. cardiologist/sonographer readers for misclassification (**Figure 4**). In the results, DL had relatively low ratios of misclassification of RCA except for the Xception model. In addition, DL also had relatively low ratios of misclassification in the control group.

Moreover, we have selected the top 10 misclassified cases of RWMA by DL (ResNet) and cardiologist/sonographer readers. Interestingly, they are cases in which cardiologist/sonographer readers and DL misclassification were very similar. DL and cardiologist/sonographer readers' misclassification matched in 8 out of 10 cases. Thus, we reasoned that the DL read was similar to the cardiologist/sonographer read. In addition, the patients' characteristics with misclassification by the DL were shown in Supplement 3. There was no statistically difference between correct classified group and misclassified group, but LV size (LVEDVi) was slightly larger in misclassified group than in correct classified group. One possible explanation is that the sample size with large LV size for development of DL model is relatively small. We may need the worsen cases for development of DL model in the further study.

For detection of territories of wall motion abnormality in the separate validation group of 40 patients from the independent site, the AUC by the DL algorithm was 0.90. The AUC was slightly smaller than the AUC in the original cohort. One explanation is that the original cohort had the equal distribution in each territory, the relatively low prediction performance in the classification was seen for the LAD asynergy, and the number of LAD asynergy was the largest in the newly gathered data.

Discussion

Interpretation of wall motion abnormalities with echocardiography is observer-dependent and requires experience. An inexperienced reader sometimes misinterprets a wall motion abnormality, and significant training is required to become expert. DL algorithm is an objective method with no intra-observer error, and its accuracy is similar to that of visual assessment by experts. The diagnostic system can be used as a useful tool to classify RWMA in clinical evaluation. However, since the number of patients examined was limited, the present study should be considered a proof of concept, and we believe that larger prospective multicenter studies are warranted.

C***omparison with previous automated analysis.*** The use of quantitative assessment was expected to improve the accuracy and objectivity of echocardiographic image analysis. Several methods for measuring cardiac wall motion, strain and strain rate were developed to be performed with echocardiographic images (28-30). However, the reproducibility of quantitative measurements in echocardiography was limited by inter- or intra-observer variability. Recently, several groups have developed automated algorithms for the analysis of left ventricular function and endocardial border detection (31,32). However, most of them remain semi-automatic where the observer input is initially needed to manually annotate important landmarks (e.g., mitral plane, apex). Fully automated assessment is needed to obtaining quantitative results without any user interaction (e.g., markers positioning, contours drawing or modification). Our results demonstrate that DCNN can be trained to identify wall motion abnormality on echocardiographic images. The accuracy of DL algorithm is superior to inexperienced observers and is similar to expert observers. We believed this study is a milestone to apply the DL algorithm for echocardiographic images in the future.

Deep learning for Echocardiography. Previous machine learning approaches, requiring the extraction and integration of pre-identified imaging measurements, have shown automated and performance in cardiovascular disease (6). In this study, we developed an objective classification model for RWMAs based on a deep learning algorithm. Although we had a relatively small number of cases with images, we were able to improve performance using this algorithm. The learned structure that resulted showed that it was possible to approve the good agreement between DL diagnosis and expert consensus. Using a simple and available algorithm, we achieved great performance accuracy. It is possible that further significant improvements with DL could be achieved by the integration of additional imaging and clinical data. We were looking into how these encouraging results could help less-experienced observers improve their diagnostic accuracy, because the agreement between less-experienced observers and the experts is often low. In addition, resident readers had a relatively high ratios of misclassification to DL algorithm (ResNet) for RCA and LCX (RCA: odds ratio: 3.9, LCX: odds ratio: 2.2). Thus, DL algorithms may have a potential to help diagnosis for RCA and LCX territories.

Although there were advantages of using deep learning for echocardiography, the major limitation of DL is that echocardiographic images were a non-structured data set. The image quality depends on the machine vendors and software version. In the clinical setting, we have used several vendors with many versions. Thus, the normalization of images between vendors will be required when we apply this algorithm in the clinical setting using many vendors.

Another limitation of DL is that the reason of different DL methods may behave differently is unclear. In our study, we apply five deep learning models to differentiate echocardiographic images. Basically, the number of parameters and layers are difference among the DL models employed in this study. One of the advantages in use of a DL model over the other types of machine learning model is that the DL can construct the appropriate features automatically developed in the intermediate layers. The extracted features may be different among the DL models because of the different numbers of parameters and layers. On the other hand, this may also make a reason why a specific model is superior to the other one unclear. Unfortunately, there is no clear explanation in this field (one of the engineering issues).

Clinical Implications. Interpretation of wall motion abnormalities with echocardiography is observer-dependent and requires experience. Assessment of RWMAs using the DL algorithm is an objective method with no intra-observer error, and its accuracy was equal to that of assessment by expert consensus. Echocardiographic assessment in artificial intelligence may be not necessary for experts; however, quantitative assessment is another advantage of artificial intelligence. In the future, we plan to expand our classification to identify different levels of RWMAs at the segment level and include images from stress echocardiography. We would also like to apply an algorithm to differentiate for several cardiovascular diseases.

Limitations. This study of deep learning applied to echocardiographic data has several limitations. First, RWMA assessment is based on results of echocardiograph, coronary angiography and left ventriculography by expert consensus. Second, we used echocardiographic images at mid-level short axis view only, acquired in only one cycle to ensure applicability to a simple imaging protocol used in clinical routine. The identification of apical abnormalities has not been tested and, patients were chosen with infarcts involving the mid segments. Possibly, a larger set of training data could allow further improvement (33). Third, the echocardiographic images do not consist of structured data and cannot reconfigure. Thus, the accuracy of diagnosis may be influenced by the image quality. Fourth, we have gathered patients with single-vessel disease in this study, we were unable to assess patients with multi-vessel disease. In the further big-data study, multi-vessel coronary disease might be included. Fifth, the number of patients was relatively limited. Generally, deep learning algorithms require thousands of patients with 10x images. On the other hand, in our analysis, the DL diagnostic accuracy seemed to be good in the independent test cohort. We believe that this report can serve as an impetus for a large multicenter-study in the future. Our results confirm in principle that DCNN may be very informative to interpret regional wall motion abnormalities, but larger numbers of patients should be performed to assess the efficacy of the automatic classification system in the clinical setting.

Conclusions. Our results support the possibility of DCNN use for automated diagnosis of myocardial ischemia in the field of echocardiography.

Clinical Perspectives:

COMPETENCY IN MEDICAL KNOWLEDGE: A deep learning algorithm is an objective method with no intra-observer error, and its accuracy seems to be equal or superior to that of visual assessment by experts.

COMPETENCY IN PATIENT CARE AND PROCEDURAL SKILLS: Regional wall motion abnormality should be carefully assessed in the clinical setting. Our results suggest that a deep learning algorithm is a useful method to detect regional wall motion abnormalities in patients with suspected coronary artery disease.

TRANSLATIONAL OUTLOOK: Although this study suggests a utility of detecting regional wall motion abnormalities by a deep learning algorithm, this deep learning model should be improved upon with a larger cohort of coronary artery disease patients.

Disclosures: None.

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References:

1. Amsterdam EA, Wenger NK, Brindis RG et al. 2014 AHA/ACC Guideline for the Management of Patients with Non-ST-Elevation Acute Coronary Syndromes: a report of the American College of Cardiology/American Heart Association Task Force on Practice Guidelines. J Am Coll Cardiol 2014;64:e139-e228.
2. Roffi M, Patrono C, Collet J-P et al. 2015 ESC Guidelines for the management of acute coronary syndromes in patients presenting without persistent ST-segment elevation. European Heart Journal 2016;37:267-315.
3. Parisi AF, Moynihan PF, Folland ED, Feldman CL. Quantitative detection of regional left ventricular contraction abnormalities by two-dimensional echocardiography. II. Accuracy in coronary artery disease. Circulation 1981;63:761-767.
4. Amundsen BH, Helle-Valle T, Edvardsen T et al. Noninvasive myocardial strain measurement by speckle tracking echocardiography: validation against sonomicrometry and tagged magnetic resonance imaging. J Am Coll Cardiol 2006;47:789-93.
5. Kusunose K, Yamada H, Nishio S et al. Validation of longitudinal peak systolic strain by speckle tracking echocardiography with visual assessment and myocardial perfusion SPECT in patients with regional asynergy. Circ J 2011;75:141-7.
6. Qazi M, Fung G, Krishnan S et al. Automated Heart Wall Motion Abnormality Detection from Ultrasound Images Using Bayesian Networks. IJCAI, 2007:519-525.
7. LeCun Y, Bengio Y, Hinton G. Deep learning. Nature 2015;521:436-44.
8. Esteva A, Kuprel B, Novoa RA et al. Dermatologist-level classification of skin cancer with deep neural networks. Nature 2017;542:115.
9. Gulshan V, Peng L, Coram M et al. Development and Validation of a Deep Learning Algorithm for Detection of Diabetic Retinopathy in Retinal Fundus Photographs. JAMA 2016;316:2402-2410.
10. Shen D, Wu G, Suk HI. Deep Learning in Medical Image Analysis. Annu Rev Biomed Eng 2017;19:221-248.
11. SUZUKI K. Machine learning in medical imaging before and after introduction of deep learning. Medical Imaging and Information Sciences 2017;34:14-24.
12. Kida S, Nakamoto T, Nakano M et al. Cone Beam Computed Tomography Image Quality Improvement Using a Deep Convolutional Neural Network. Cureus 2018;10.
13. Shrestha S, Sengupta PP. Imaging Heart Failure With Artificial Intelligence. 2018.
14. Betancur J, Commandeur F, Motlagh M et al. Deep learning for prediction of obstructive disease from fast myocardial perfusion SPECT: a multicenter study. JACC: Cardiovascular Imaging 2018.
15. Sanchez-Martinez S, Duchateau N, Erdei T et al. Machine Learning Analysis of Left Ventricular Function to Characterize Heart Failure With Preserved Ejection Fraction. Circulation: Cardiovascular Imaging 2018;11:e007138.
16. Tabassian M, Sunderji I, Erdei T et al. Diagnosis of Heart Failure With Preserved Ejection Fraction: Machine Learning of Spatiotemporal Variations in Left Ventricular Deformation. Journal of the American Society of Echocardiography 2018.
17. Jordan MI, Mitchell TM. Machine learning: Trends, perspectives, and prospects. Science 2015;349:255-260.
18. Amari S. The handbook of brain theory and neural networks: MIT press, 2003.
19. Zeiler MD, Fergus R. Visualizing and understanding convolutional networks. European conference on computer vision: Springer, 2014:818-833.

20. Zhang J, Gajjala S, Agrawal P et al. Fully Automated Echocardiogram Interpretation in Clinical Practice. Circulation 2018;138:1623-1635.
21. Lang RM, Badano LP, Mor-Avi V et al. Recommendations for cardiac chamber quantification by echocardiography in adults: an update from the American Society of Echocardiography and the European Association of Cardiovascular Imaging. J Am Soc Echocardiogr 2015;28:1-39 e14.
22. Ryan T, Berlacher K, Lindner JR, Mankad SV, Rose GA, Wang A. COCATS 4 Task Force 5: training in echocardiography. Journal of the American College of Cardiology 2015;65:1786-1799.
23. Chollet F. Xception: Deep learning with depthwise separable convolutions. arXiv preprint 2017:1610.02357.
24. Szegedy C, Vanhoucke V, Ioffe S, Shlens J, Wojna Z. Rethinking the inception architecture for computer vision. Proceedings of the IEEE conference on computer vision and pattern recognition, 2016:2818-2826.
25. Deng J, Dong W, Socher R, Li L-J, Li K, Fei-Fei L. Imagenet: A large-scale hierarchical image database. Computer Vision and Pattern Recognition, 2009 CVPR 2009 IEEE Conference on: Ieee, 2009:248-255.
26. Ciresan DC, Meier U, Gambardella LM, Schmidhuber J. Convolutional neural network committees for handwritten character classification. Document Analysis and Recognition (ICDAR), 2011 International Conference on: IEEE, 2011:1135-1139.
27. DeLong ER, DeLong DM, Clarke-Pearson DL. Comparing the areas under two or more correlated receiver operating characteristic curves: a nonparametric approach. Biometrics 1988;44:837-45.
28. Mor-Avi V, Vignon P, Koch R et al. Segmental analysis of color kinesis images: new method for quantification of the magnitude and timing of endocardial motion during left ventricular systole and diastole. Circulation 1997;95:2082-2097.
29. Urheim S, Edvardsen T, Torp H, Angelsen B, Smiseth OA. Myocardial strain by Doppler echocardiography: validation of a new method to quantify regional myocardial function. Circulation 2000;102:1158-1164.
30. Amundsen BH, Helle-Valle T, Edvardsen T et al. Noninvasive myocardial strain measurement by speckle tracking echocardiography: validation against sonomicrometry and tagged magnetic resonance imaging. Journal of the American College of Cardiology 2006;47:789-793.
31. Leung KE, Bosch JG. Automated border detection in three-dimensional echocardiography: principles and promises. European journal of echocardiography 2010;11:97-108.
32. Yang L, Georgescu B, Zheng Y, Foran DJ, Comaniciu D. A fast and accurate tracking algorithm of left ventricles in 3D echocardiography. Proceedings/IEEE International Symposium on Biomedical Imaging: from nano to macro IEEE International Symposium on Biomedical Imaging: NIH Public Access, 2008:221.
33. Narula S, Shameer K, Omar AMS, Dudley JT, Sengupta PP. Reply: deep learning with unsupervised feature in echocardiographic imaging. Journal of the American College of Cardiology 2017;69:2101-2102.

Figure legends:

Figure 1: Import Data: Total 400 cases with 1200 images were split with 256 cases (786 images) as the training set, 64 cases (192 images) as the validation set, and 80 cases (240 images) as the test set.

Figure 2: Training and Validation: The model converges in the training process near the100th epoch, and the data distributions were narrow range.

Figure 3: Diagnostic Ability to Detect the Presence of Regional Wall-motion Abnormalities: The area under the curves by several deep learning algorithms for detection of territories of wall motion abnormality were good.

Figure 4: Odds Ratio of Misclassification for Deep Learning vs. Cardiologists / sonographers: Deep learning had relatively low ratios of misclassification of RCA except for the Xception model.

Central Illustration: Neural Networks for the Presence of Regional Wall-motion Abnormalities and the Territory of Regional Wall-motion Abnormalities: The fully connected layers transform the image features into the final scores, by adjusting weights for neuron activations during training.

Supplement 1: Diagnostic ability to detect the presence of regional wall-motion abnormalities by ResNet, cardiologists/sonographers, and residents.

Supplement 2: AUCs for three territories

Supplement 3: Background of misclassified cases.

Table 1: Baseline characteristics of the study population

	Control	LAD	LCX	RCA
Number	100	100	100	100
Age, yrs	70 ± 7	69 ± 11	73 ± 11	69 ± 11
Male, n	62	76	69	74
Heart rate, bpm	72 ± 15	71 ± 13	71 ± 13	71 ± 14
LVEDVi, ml/m^2	55 ± 14	74 ± 28*	64 ± 17*†	60 ± 18†
LVESVi, ml/m^2	20 ± 6	42 ± 24*	30 ± 12*†	26 ± 12†
WMSI	0	1.5 ± 0.4*	1.3 ± 0.3*†	1.2 ± 0.2*†‡
LVEF, %	64 ± 4	47 ± 12*	53 ± 8*†	56 ± 10*†

* $p < 0.05$, vs. Control, †$p < 0.05$, vs. LAD, ‡$p < 0.05$, vs. LCX.

Data are presented as number of patients (percentage), mean ± SD. Abbreviations: CAD, coronary artery disease; LAD, left anterior descending, LCX, left circumflex, RCA, right coronary artery; LVEDVi, left ventricular end diastolic volume index; LVESVi, left ventricular end systolic volume index; WMSI, wall motion score index; LVEF, left ventricular ejection fraction,

Figure 1: Import data

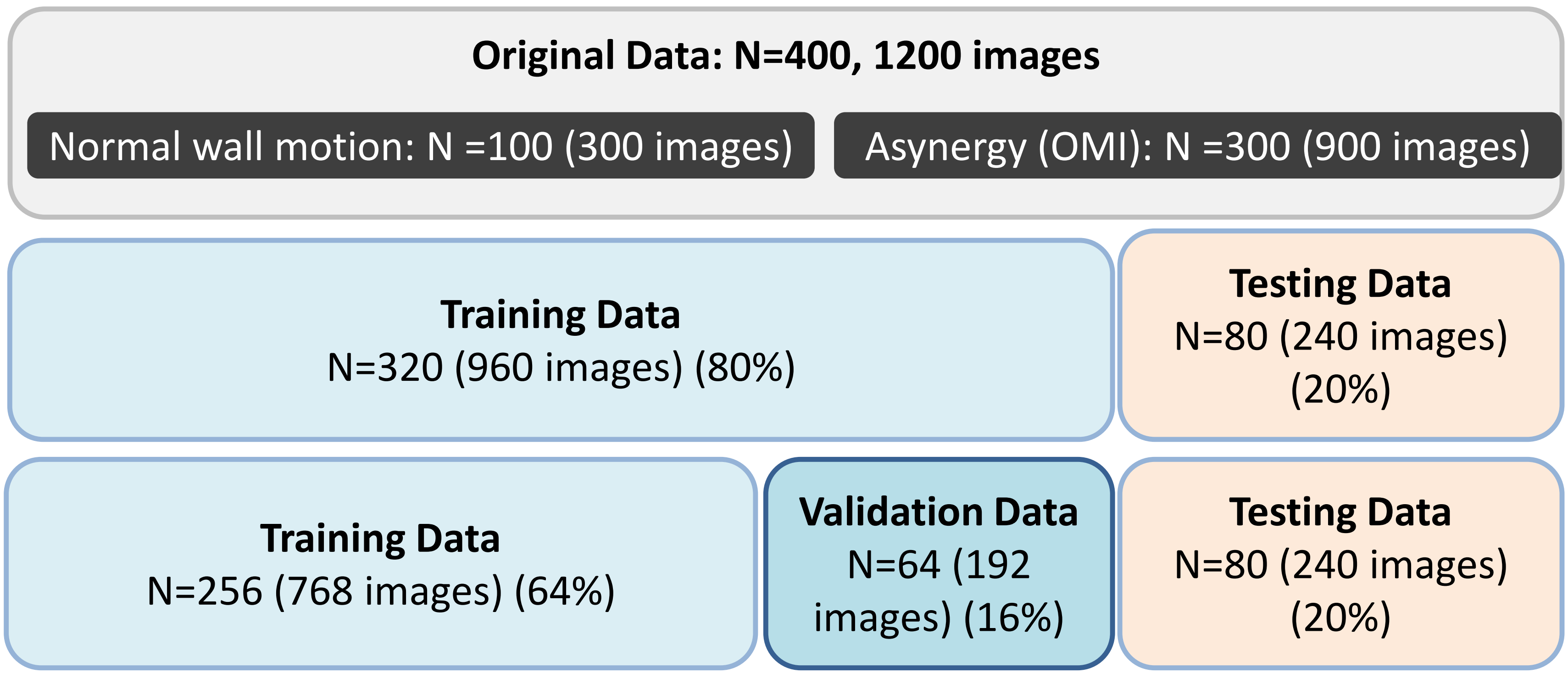


Figure 2: Training and Validation

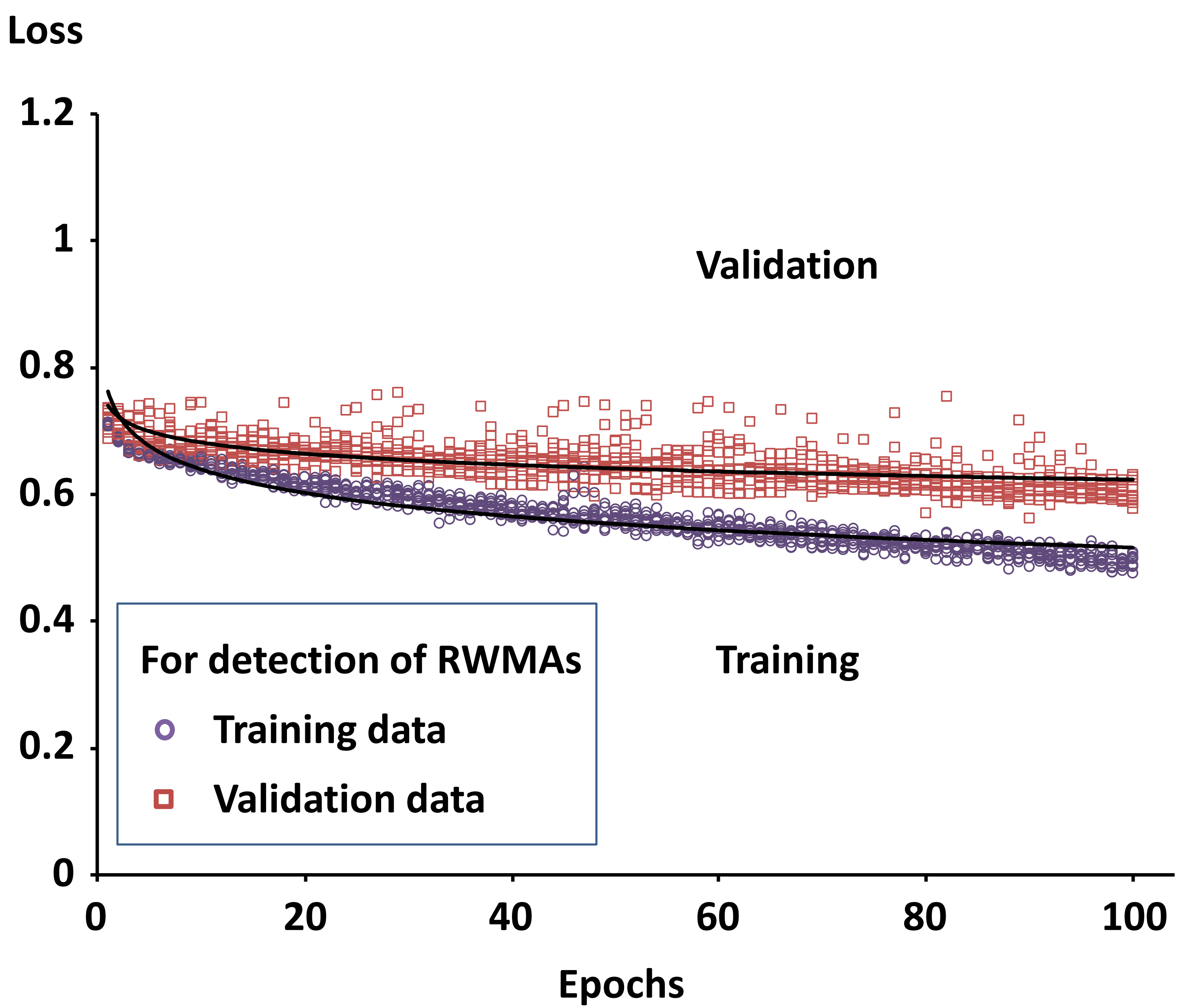


Figure 3: Diagnostic ability for detecting the territory of regional wall motion abnormalities

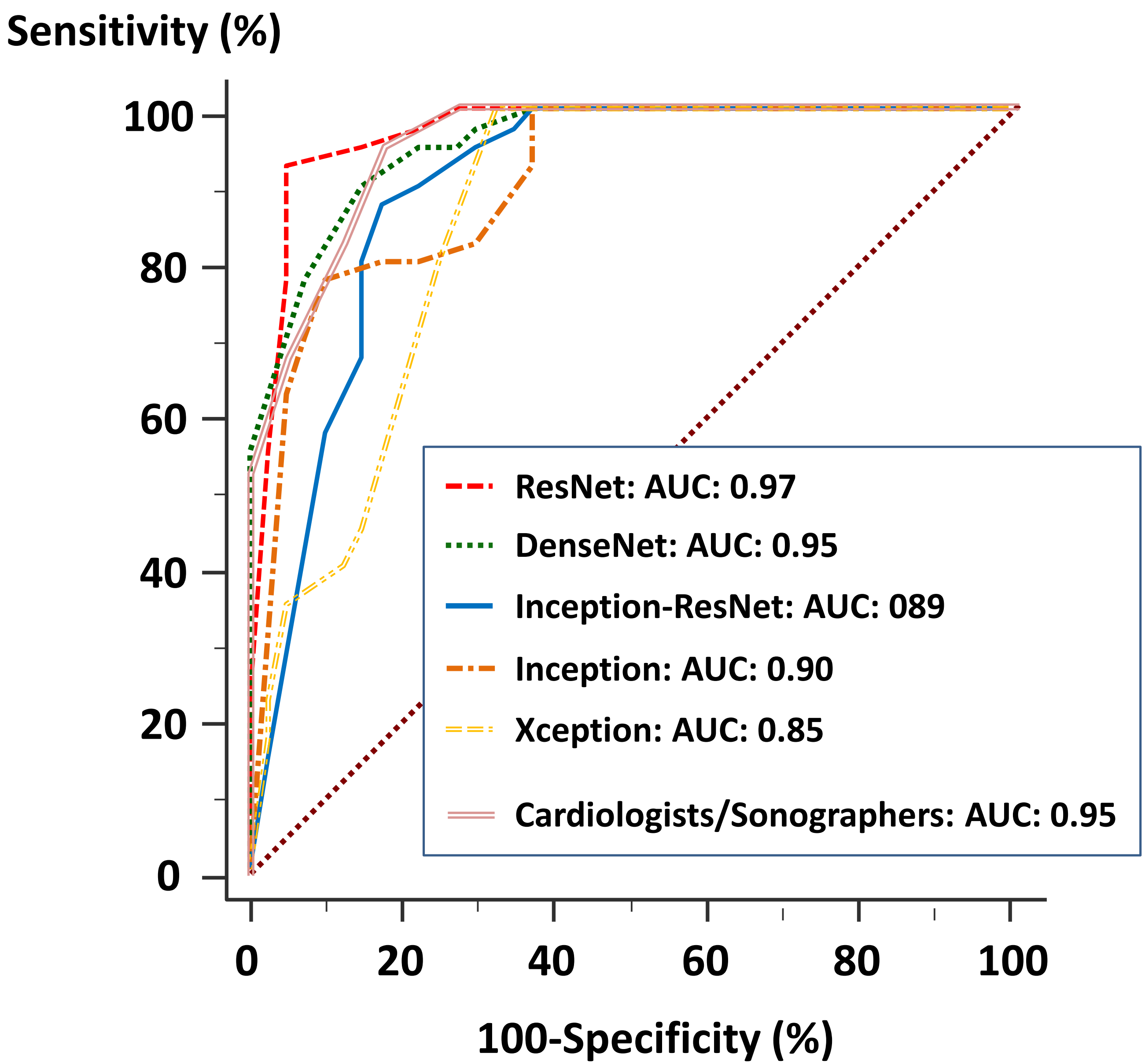
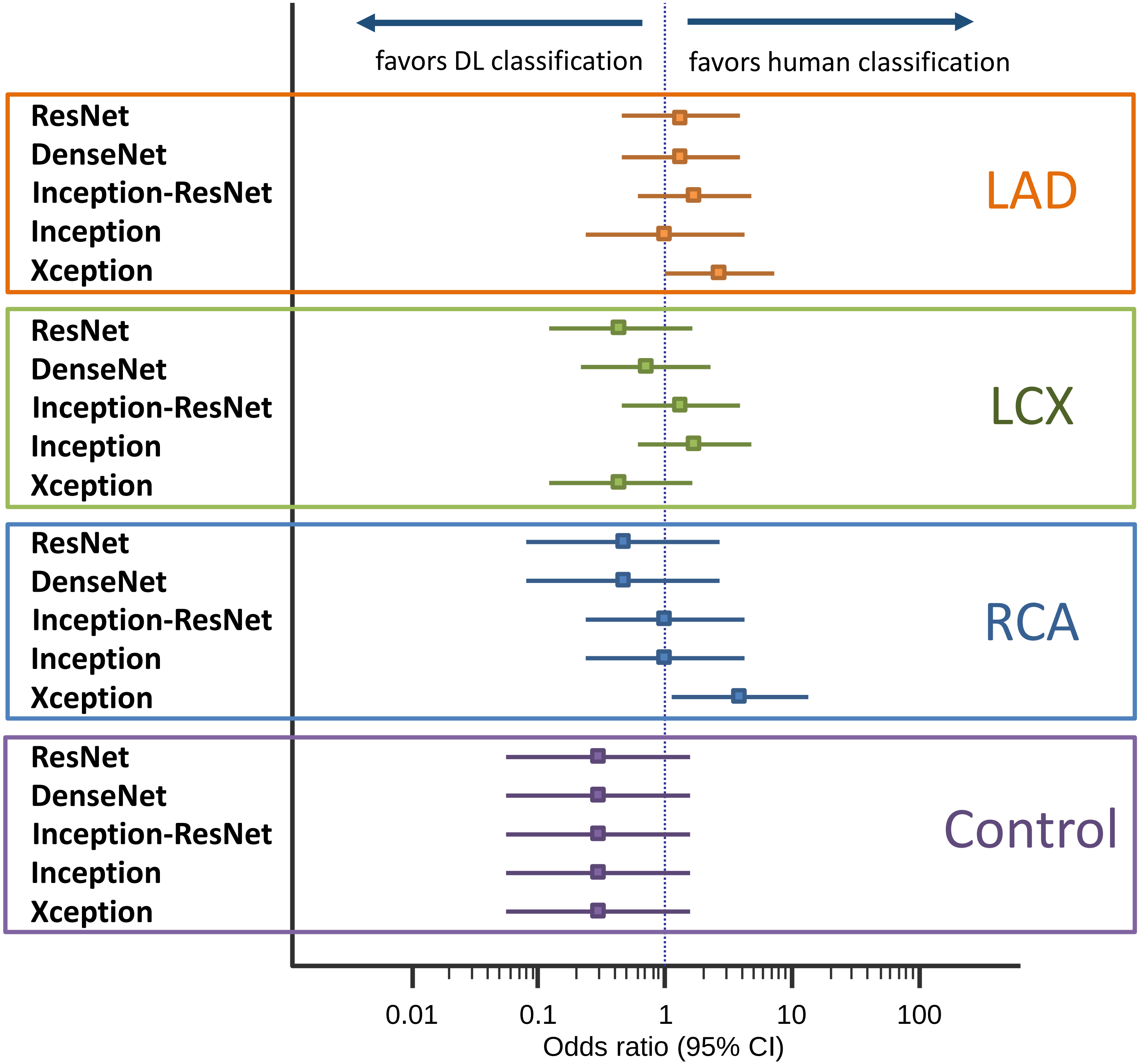


Figure 4: Odds ratio of misclassification for DL vs. Human



Central Illustration: Neural network for the regional wall-motion abnormalities