REVIEW ARTICLE

Recognition of Fetal Facial Expressions Using Artificial Intelligence Deep Learning

Yasunari Miyagi[1], Toshiyuki Hata[2], Saori Bouno[3], Aya Koyanagi[4], Takahito Miyake[5]

Abstract

Fetal facial expressions are useful parameters for assessing brain function and development in the latter half of pregnancy. Previous investigations have studied subjective assessment of fetal facial expressions using four-dimensional ultrasound. Artificial intelligence (AI) can enable the objective assessment of fetal facial expressions. Artificial intelligence recognition of fetal facial expressions may open the door to the new scientific field, such as "AI science of fetal brain", and fetal neurobehavioral science using AI is at the dawn of a new era. Our knowledge of fetal neurobehavior and neurodevelopment will be advanced through AI recognition of fetal facial expressions. Artificial intelligence may be an important modality in current and future research on fetal facial expressions and may assist in the evaluation of fetal brain function.

Keywords: Artificial intelligence, Deep learning, Facial recognition, Fetus, Machine learning, Ultrasonography.

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Introduction

Fetal behaviors such as fetal movements and facial expressions that have been observed by four- (4D) or three-dimensional (3D) ultrasound have been deemed to be related to the development of fetal central nervous system development.[1–11] A scoring system,[12] which was originally reported by Kurjak et al. and later modified by Stanojevic et al.,[13] can evaluate fetal neurobehavioral development by evaluating fetal movements and facial expressions. Fetal facial movements and expressions such as blinking, a face without any expression, mouthing, scowling, smiling, sucking, tongue expulsion, and yawning can be evaluated by 4D ultrasound from the beginning of the 2nd trimester of pregnancy.[2,14] Eye blinking (blinking) is a reflex response possibly related to brain function maturation and development that occurs with advancing gestation.[14–18] Mouthing is the most frequent expression and is recognized as fetal brain maturation if it occurs together with non-rapid eye movement after 35 weeks of gestation.[19] The frequency of scowling that might indicate suffering of the fetus in utero pain or stress[20] increases with advancing gestation.[21] Smiling might indicate a state of brain development performing complex facial movements.[22,23] The correlation of an expressionless face and tongue expulsion with brain function is unclear.[14] Yawning may be utilized as an index of fetal development.[24,25] Therefore, it is important to investigate fetal facial expressions. There have been, however, no standard objective methods to evaluate fetal facial expressions.

Recently, artificial intelligence (AI) has advanced into the field of medicine. In different fields of obstetrics and gynecology, research works relevant to AI have been published.[26–35] A well-trained AI classifier that can evaluate and classify fetal facial expressions would help investigate the development of the fetal central nervous system. The AI recognition of adult facial expressions has been investigated. Kim et al. reported the accuracy of the AI facial expression recognition was 0.965.[36] Adult facial expressions can state human mental state and behavior and their analysis is available for marketing, healthcare, safety, environment, and social media.[37]

In this review article, we introduce the updated status of AI recognition of fetal facial expressions as a significant parameter for fetal brain function and suggest recommendations for future research on fetal brain development and function.

[1]Department of Gynecology, Miyake Ofuku Clinic, Okayama, Japan; Medical Data Labo, Okayama, Japan; Department of Gynecologic Oncology, Saitama Medical University International Medical Center, Hidaka, Japan

[2]Department of Obstetrics and Gynecology, Miyake Clinic, Okayama, Japan; Department of Perinatology and Gynecology, Kagawa University Graduate School of Medicine, Kagawa, Japan

[3,4]Department of Obstetrics and Gynecology, Miyake Clinic, Okayama, Japan

[5]Department of Gynecology, Miyake Ofuku Clinic, Okayama, Japan; Department of Obstetrics and Gynecology, Miyake Clinic, Okayama, Japan; Department of Perinatology and Gynecology, Kagawa University Graduate School of Medicine, Kagawa, Japan

Corresponding Author: Yasunari Miyagi, Department of Gynecology, Miyake Ofuku Clinic, Okayama, Japan; Medical Data Labo, Okayama, Japan; Department of Gynecologic Oncology, Saitama Medical University International Medical Center, Hidaka, Japan, Phone: +81-86-281-2020, e-mail: ymiyagi@mac.com

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Recognition of Fetal Facial Expressions Using AI

All data per fetus are divided into test/training/validation datasets at random in a ratio that is not fixed but commonly set to 0.20/0.64/0.16. In this way, training datasets, validation datasets, and non-overlapping test datasets are created.

The AI classifier is then designed. The AI classifier composed of convolutional neural network (CNN)[38–43] for classifying categories is often used for image recognition. The CNN usually comprises layers with a combination of convolutional layers such as pooling layers,[44–46] linear layers,[47,48] flattened layers,[49] batch normalization layer,[50] rectified linear unit layers,[51,52] and softmax layer[53,54] that presents the probabilities of each category named confidence scores. Then, the category with the highest confidence score is determined as the AI classification category of each image. The AI classifier is trained using the training dataset with simultaneous validation by using the validation dataset. Before the AI training, the training and validation datasets are augmented by methods such as rotating the images. Data augmentation is often used, because image processing such as rotation, can result in different vector data in the same category.[31]

The feasibility of the AI classifier is evaluated using the test dataset. Then, statistical values of the test dataset are then obtained, such as sensitivity, specificity, accuracy, receiver operating characteristic (ROC) curve, etc.

Previous Studies on AI Recognition of Fetal Facial Expressions

The development of the AI classifier with the original neural network architecture that recognizes and classifies images of fetal faces captured by sonography was reported by Miyagi et al.[55] This pilot study was the first report on the recognition of fetal facial expressions by AI, to the best of our knowledge. The CNN architecture consisted of 13 layers; 2 convolution layers, 3 rectified linear unit layers, 2 pooling layers, 1 flatten layer, 3 linear layers, 1 batch normalization layer, and 1 softmax layer. The classifier could classify only five categories: blinking, face without any expression (neutral face), mouthing, scowling, and yawning, due to sample limitations for each category. The number of fetus/images were 93/922 and the number of test/validation/training datasets for creating the AI was 222/1,648/7,168. The accuracy for the test dataset was 0.985. The values of accuracy/sensitivity/specificity were 0.996/0.993/1.000, 0.992/0.986/1.000, 0.985/1.000/0.979, 0.996/0.888/1.000, and 1.000/1.000/1.000 for blinking, mouthing, neutral face, scowling, and yawning, respectively. Though the confidence score of the blinking category in the rated categories was 0.51 $\pm$ 0.35 (mean $\pm$ SD), the maximum values of the average of the confidence scores of other categories were over 0.85.

Further Achievements in AI Recognition of Fetal Facial Expressions

We introduce the improved AI classifier composed of the same neural network architecture by collecting more data for recognizing seven categories in this review. The number of fetus/images were 237/1,457 and the number of test/validation/training dataset for creating the AI was 251/1,536/11,248. The accuracy, the confidence scores, and the ROC curve of the AI fetal facial expression analysis were 0.996 as shown Figures 1 to 3, respectively. The accuracy/sensitivity/specificity values were 0.996/0.964/1.000, 1.000/1.000/1.000, 0.996/1.000/0.994, 1.000/1.000/1.000, 1.000/1.000/1.000, 1.000/1.000/1.000, and 1.000/1.000/1.000 for blinking, mouthing, neutral face, scowling, smiling, tongue expulsion, and yawning, respectively (Table 1). Other statistical values such as negative predictive value, positive predictive value, informedness, the area under the ROC curve, F1 score, markedness, and Matthews correlation coefficient were over 0.96 in all categories. Sample images classified by AI are shown in Figure 4.

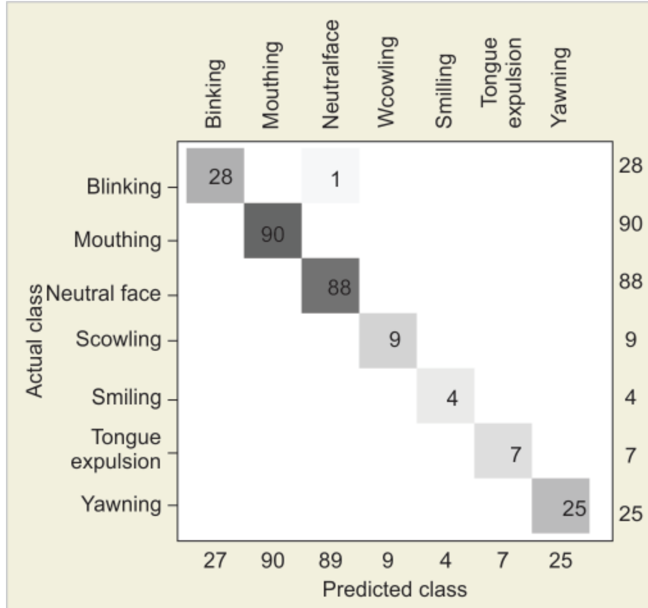

Fig. 1: The confusion matrix plot for the test dataset. The correct predictions were located in a diagonal matrix position. The accuracy for classifying fetal facial expression for seven categories was 0.996

Limitations

The following limitations of AI fetal facial expression recognition need to be considered. First, the AI cannot properly classify unknown images. Though seven facial categories were used, there would be other fetal facial expressions that are significant in investigating the development of the fetal central nervous system. The perfect classification of fetal facial expressions has not yet been established, possibly due to the long time needed to observe the fetal face and lack of consensus image classification by examiners. Such undefined and undiscovered images and categories would be needed to train AI for clinical practice and research in the future. Second, the feasibility of fetal facial expression recognition by AI depends on the supervised data by experienced examiners. Moreover, the anthropometric differences affected in fetal facial expression could strongly affect AI creation, this AI would not be feasibly used for different anthropometric fetuses directly. We believe, however, that similar algorithms would be available for other anthropometric fetuses. Third and last, although the AI showed quite good accuracy, there are still defective datasets such as for sucking that was rarely seen during the examination. The incidence of sucking was approximately 1% in all cases.[55]

More datasets are required, as in general, AI deep learning for the neural network is better with more datasets. The recognition frequencies and accuracies of each fetal facial expression related to gestational weeks by AI should also be analyzed.

Further Perspective

The advantage of multi-modalities for AI has been presented in the classification of the uterine cervical squamous epithelial lesion from colposcopy images combined with HPV types[27] and the predicting live birth from blastocyst images combined with the conventional clinical embryo evaluation parameters.[29] Therefore, fetal facial expressions can be classified by image and by incorporating images with gestational age and other associated parameters.

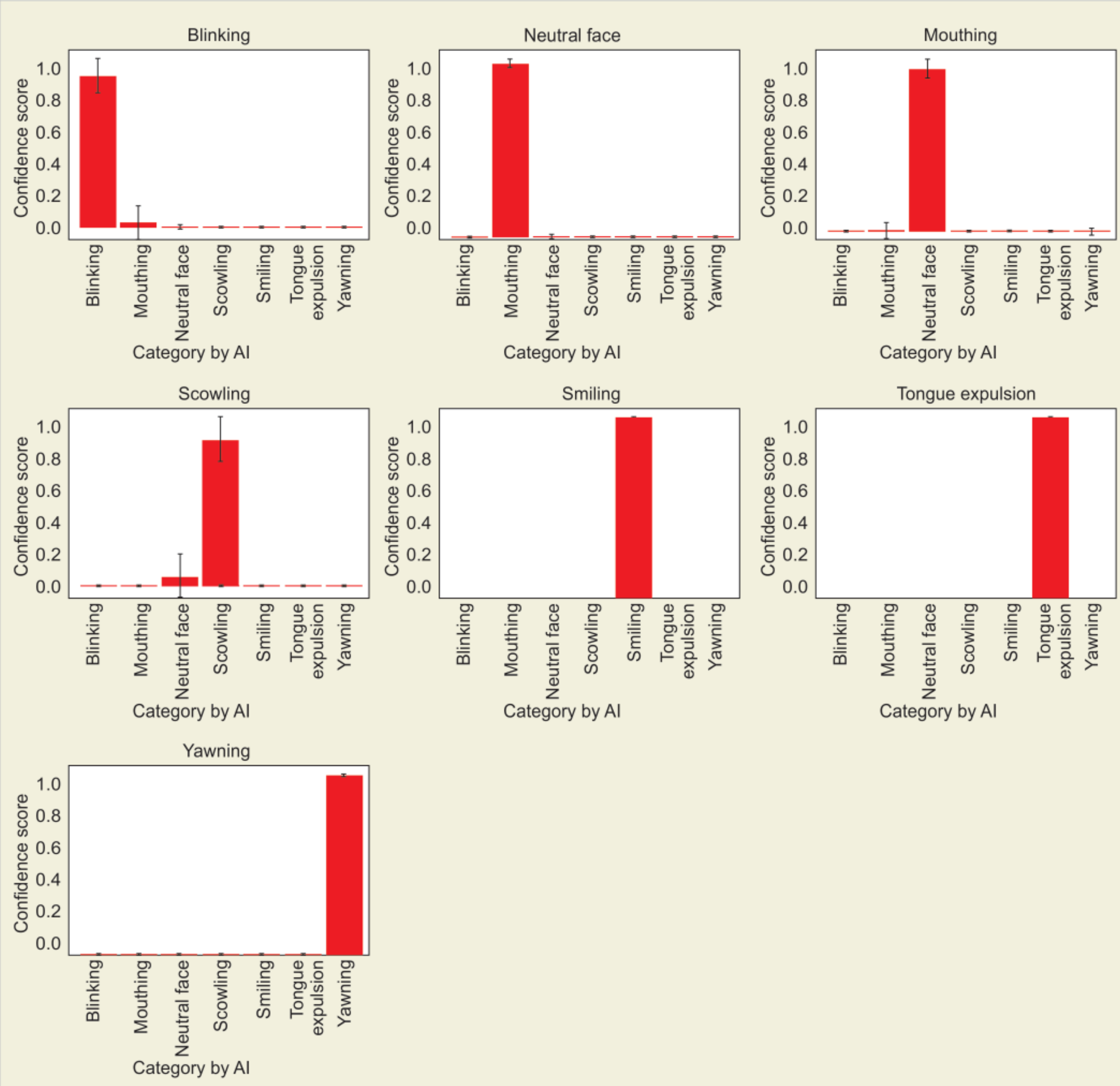

Fig. 2: The profiles of the confidence scores for each category per image (mean ± standard deviation) for the test dataset

Established AI has no intrinsic bias for classifying images. Thus, AI can show objective findings regarding fetal facial expression recognition, which could advance research on the fetal central nervous system and brain development. The establishment of AI classification of fetal facial expressions could enable objective fetal neurodevelopment investigation by applying tests such as mini KANET that is used for predicting postnatal developmental disabilities.[56] Further establishment of an advanced AI recognition for fetal facial expression using incorporated images with associated parameters will be able to reveal correlations between facial expressions and parameters such as fetal physical development, multiple pregnancies, parity, siblings, maternal personality, maternal disease, mental and physical development after birth, personality formation, score in school, intelligence, etc. Subsequent observation data of medical and social factors obtained in cohort studies or retrospective studies may aid mothers in the next generation in providing optimal treatment for their fetuses.

Conclusion

As the fetal facial expression is considered to be important for non-invasively investigating the fetal central nervous system and brain development, AI may be useful in this aspect with the advent of 4D ultrasound.

Table 1: Statistic results of AI for classifying fetal facial expressions

	Fetal facial expression						
Statistic results	*Eye blinking*	*Neutral face*	*Mouthing*	*Scowling*	*Smiling*	*Tongue expulsion*	*Yawning*
True-positive number	27	88	90	9	4	7	25
True-negative number	223	162	161	242	247	244	226
False-positive number	0	1	0	0	0	0	0
False-negative number	1	0	0	0	0	0	0
Accuracy	0.996	0.996	1.000	1.000	1.000	1.000	1.000
Area under ROC curve	1.000	1.000	1.000	1.000	1.000	1.000	1.000
F1 score	0.982	0.994	1.000	1.000	1.000	1.000	1.000
False discovery rate	0.000	0.011	0.000	0.000	0.000	0.000	0.000
False-negative rate	0.036	0.000	0.000	0.000	0.000	0.000	0.000
False-positive rate	0.000	0.006	0.000	0.000	0.000	0.000	0.000
Informedness	0.964	0.994	1.000	1.000	1.000	1.000	1.000
Markedness	0.996	0.989	1.000	1.000	1.000	1.000	1.000
Matthews correlation coefficient	0.980	0.991	1.000	1.000	1.000	1.000	1.000
Negative predictive value	0.996	1.000	1.000	1.000	1.000	1.000	1.000
Positive predictive value (precision)	1.000	0.989	1.000	1.000	1.000	1.000	1.000
Sensitivity (recall)	0.964	1.000	1.000	1.000	1.000	1.000	1.000
Specificity	1.000	0.994	1.000	1.000	1.000	1.000	1.000

ROC, receiver operating characteristic

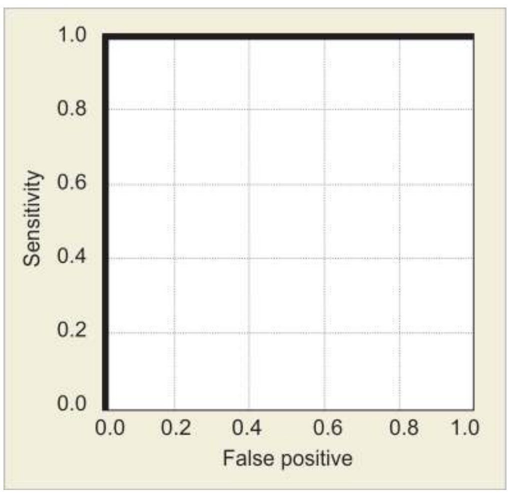

Fig. 3: The receiver operating characteristic (ROC) curve of AI for the test dataset. The area under the ROC curve was 1.0

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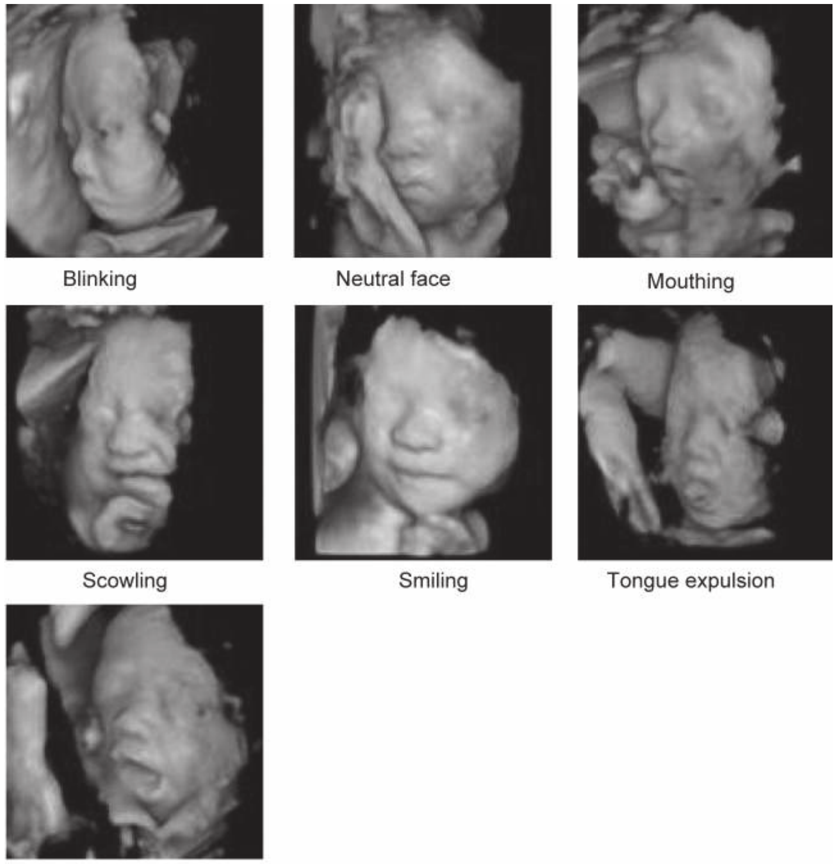

Fig. 4: Sample images classified by AI. The accuracy for classifying fetal facial expression for seven categories was 0.996, which was almost equivalent to human classification

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