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Editorial

Artificial Intelligence Techniques for Electronics

Gwanggil Jeon [1,2]

[1] Department of Embedded Systems Engineering, Incheon National University, 119 Academy-ro, Yeonsu-gu, Incheon 22012, Republic of Korea; gjeon@inu.ac.kr
[2] Energy Excellence & Smart City Lab, Incheon National University, 119 Academy-ro, Yeonsu-gu, Incheon 22012, Republic of Korea

1. Introduction

Artificial intelligence technology has become an indispensable element in the field of electronics, and its influence is enormous. Artificial intelligence can be applied to various research fields and it is a powerful tool that is applicable to signal processing, power electronics design, simulation, control, estimation, fault diagnosis, and fault tolerance control.

This editorial introduces 12 applications of artificial intelligence. These papers have made great contributions to artificial-intelligence-based modeling, labeling, data construction, and quality.

2. Overview of Contributions

In computer vision, CNN technology based on artificial intelligence is widely used. In particular, in areas such as the Internet of Things, drones, and image sensing, there is a growing demand for computing processing at the edge due to communication problems. Low-cost microcontrollers are a promising solution in terms of their cost effectiveness. In the contribution by Orășan et al., "A Brief Review of Deep Neural Network Implementations for ARM Cortex-M Processor", the authors conducted a study on the implementation of a deep neural network using an ARM Cortex-M core-based low-cost microcontroller [1]. On the other hand, there is a lot of interest in edge AI applications and DNN optimization and compression, but there are not many papers related to this research field. This paper consisted of the following three steps: (1) an application overview and the results of using DNN architecture and an ARM Cortex-M core-based microcontroller, (2) a low-cost hardware device and an SW development overview solution, and (3) a recent trend description.

Recently, interest in the use of robots in STEM education has increased. However, since robots are expensive equipment, it is practically difficult to teach using these robots in schools. It is also difficult to obtain robots for education and to expand upon them for educational purposes. In the contribution by Chronis and Varlamis, "FOSSBot: An Open Source and Open Design Educational Robot", the authors proposed a low-cost 3D printing and integrated software-based solution that could meet the needs of students of all school ages [2]. It provided details on 3D printable robotic parts and a list of electronics that could support a wide range of educational activities and described a flexible software stack that supports four modes of operation. This would meet the needs of beginners who do not know programming, intermediate users who use block-based programming, and experts who have experience in robot control.

In the contribution by Y. Hayashi, "Emerging Trends in Deep Learning for Credit Scoring: A Review", the author improved upon the accuracy of machine learning algorithms and provided the possibility of replacing them with reliable algorithms [3]. He also analyzed why deep belief networks (DBNs) can achieve a higher accuracy than shallow networks and discussed the potential classification capabilities of DL-based classifiers. Through an analysis of studies published between 2019 and 2022, he studied why state-of-the-art DL techniques achieve a higher accuracy than ensemble classifiers, hybrids,

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rule extraction methods, and rule-based classifiers. The models reviewed in this study were tested on datasets provided from Australia, Germany, Japan, and Taiwan, and their performances were demonstrated. In addition, this paper also discussed how tabular data sets are converted into images for the application of two-dimensional convolutional neural networks, and how black box models using local and global rule extractions and rule-based methods affect reliability.

In the contribution by Akal and Barbu, "Fast 3D Liver Segmentation Using a Trained Deep Chan-Vese Model", the authors introduced a study on 3D segmentation that generalized the level set method of Chan-Vese data in various ways [4]. Chan-Vese is a refinement method that evolves a set of levels while simultaneously and locally fitting an intensity model for inner and outer regions. The contributions of this paper were as follows. First, simple length-based normalization was replaced with a Fully Convolutional Network (FCN)-based learning model. Second, two 3D deformation models based on 3D U-Net and 3D FCN were introduced. The experimental results showed that the proposed method provided faster 3D segmentation results compared to the state-of-the-art method, while requiring fewer parameters for training.

In order to use artificial-intelligence-based deep convolutional neural networks for image verification, a large amount of labeled training data is required. To improve this, the contribution by Solomon et al., "UFace: An Unsupervised Deep Learning Face Verification System", proposed an unsupervised deep learning face verification system called UFace [5]. The training process of the proposed technology was as follows. From unlabeled big data, k images that were most similar to the specified face image and k images that were least similar to the specified face image were selected and used for training. UFace was implemented using an autoencoder and Siamese network method and the latter had a better performance. Unlike normal deep neural network training, UFace calculated the loss function for each input image k times for similar images and k times for dissimilar images. The performance of UFace was evaluated on four benchmark face validation datasets (LFW, YTF, CALFW, and CFP-FP). According to the experimental results, UFace with a Siamese network achieved a 99.40%, 96.04%, 95.12%, and 97.89% accuracy on the four data sets, respectively. The biggest advantage of UFace was that it used less training data and required no labeling.

BCNN is a small to medium-sized neural network model that provides an excellent accuracy. Although BCNN is a method that greatly reduces the computational complexity of convolution with less data, a further reduction in the complexity of the BCNN model is required for faster execution. This can be achieved by reducing the number of model parameters at the cost of the model's accuracy. In the contribution by de Sousa et al., "Multi-Model Inference Accelerator for Binary Convolutional Neural Networks", the authors proposed a multi-model inference technique to reduce the execution time of the binarized inference process without a deterioration in its accuracy [6]. The authors also proposed a hardware accelerator for implementing multi-model inference throughput in embedded systems. The multi-model inference accelerator was tested on low-density Zynq-7010 and Zynq-7020 FPGA devices and image classification experiments were performed on the CIFAR-10 dataset. According to the experimental results, the proposed accelerator improved the frame rate per number of LUTs by 7.2 times in comparison to the benchmark in ZYNQ7020 FPGA. Through this, the efficiency of the proposed model and hardware accelerator could be confirmed.

Although research into explainable artificial intelligence continues, explanations of predictor behavior are still inaccurate and lacking. To improve this, in the contribution by Contreras et al., "A DEXiRE for Extracting Propositional Rules from Neural Networks via Binarization", the authors studied a tool for DEXiRE that approximated the rules of deep learning models with hidden layers [7]. DEXiRE proposed the binarization of a neural network to derive a Boolean function from a hidden layer to generate an intermediate set of rules. First, a rule set was introduced between the hidden layer and the input layer, and finally, the complete rule set was obtained by using the intermediate rule set and the antithesis of the first-layer rules. Statistically, the results were tested and the size and complexity of the data were reduced using a satisfiability algorithm. In this process, redundant, infrequently occurring, or inconsistent data were filtered out. According to the experimental results, DEXiRE was validated on six different data sets. Compared to the state-of-the-art ECLAIRE, it showed: (1) a consistent performance, (2) shorter rules, and (3) a shorter execution time.

MARL (multi-agent reinforcement learning), a type of reinforcement learning, aims to study the behavior of multiple agents in a shared environment. Existing communication-based MARL methods have two problems. First, it is assumed that there is no case of interference and it proceeds. However, interference in actual inter-agent communication often occurs. Therefore, it is necessary to consider issues such as communication stability and channel capacity restrictions. Second, it is not ready to be scaled to large multi-agent systems. To improve this, in the contribution by Zhao et al., "ACUTE: Attentional Communication Framework for Multi-Agent Reinforcement Learning in Partially Communicable Scenarios", a method called ACUTE (Attentional CommUnicaTion FramEwork) was proposed, which enabled efficient communication between agents in a dynamic environment and improved the decision making efficiency by using the most useful information from other agents [8]. The experimental results showed that the proposed model was suitable for large-scale multi-agent systems because it could efficiently utilize messages in low-reliability channels in comparison to the existing methods.

Monitoring and predicting indoor environments play important roles in obtaining big data and detecting anomalies in industrial environments and living spaces. In the contribution by Kim et al., "An Indoor Multi-Environment Sensor System Based on Intelligent Edge Computing", the authors proposed an indoor multi-environment sensor system based on intelligent edge computing that collected and predicted environmental data [9]. The proposed system collected data using 14 types of environmental sensors and an object detection technology model, and implemented a model that predicted indoor air quality based on a bidirectional LSTM network. The trained model showed a high performance in predicting the factors that deteriorate indoor air quality, such as CO2, PM2.5, and volatile organic compounds. The main contribution of this study was the proposal of an integrated approach to various functions by applying edge computing to indoor environment monitoring.

In the field of intelligent transportation, problems such as analyzing various transportation means and providing personalized transportation are major research areas. In the contribution by Drosouli et al., "TMD-BERT: A Transformer-Based Model for Transportation Mode Detection", a transformer-based sensor-data-based transportation detection model was presented [10]. The proposed transformer-based technique processed the entire data sequence, understood the importance of each part of the input sequence, and used the attention mechanism to learn the global dependencies of the sequence by assigning weights according to importance. According to the experimental results, the proposed method showed a prediction accuracy of 98.8%, which was a high performance in comparison to the state-of-the-art benchmark model.

As the credit card market grows, the marketing methods used by credit card companies to secure customers are also changing. The process of understanding individual tastes and payment patterns has become an essential element, and a personalized recommendation method for properly understanding customers' interests and meeting their needs is also required. Statistics show that personalization systems that recommend suitable products or stores to customers are effective. However, the existing research model that implements the general framework based on neural networks does not reflect the main domain information of credit card payment data when directly applied to store recommendations. To improve this, the contribution by Yoo and Kim, "Merchant Recommender System Using Credit Card Payment Data", proposed a model specialized for affiliate store recommendations by reflecting the domain information of credit card payment data [11]. The learning data included the customer's gender and age, their past card payment data, and information on the industry and region of the payment merchant, and these data were interactively learned together. According to the experimental results, the proposed NMF_CSI model showed a performance improvement of 3% based on HR@10 and 5% based on NDCG@10 in comparison to the existing model.

ABSA (Aspect-Based Sentiment Analysis) is a technique for emotion analyses. The three stages of ABSA are Aspect, Sentiment, and Emotion classification. In the contribution by Kaminska et al., "Fuzzy Rough Nearest Neighbour Methods for Aspect-Based Sentiment Analysis", a machine learning method based on a fuzzy rough set was studied [12]. The contributions of this study were as follows. It integrated three phases such as Aspect, Sentiment, and Emotion in English text, extended FRNN-OWA (Ordered Weighted Average Operators) combined with transformer-based text embedding, and applied the Fuzzy-Rough Nearest Neighbor classification technique. The experimental results showed that the proposed technique was superior when compared to a benchmark that performed the same ABSA classification on the Dutch version of the dataset.

3. Conclusions

In this editorial, 12 research results on Artificial Intelligence Techniques for Electronics were introduced. Based on the research results introduced here, it is expected that the development and research in the field of AI-based electronics will become more active in the future.

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