



Editorial

Deep Learning Applications with Practical Measured Results in Electronics Industries

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Abstract: This editorial introduces the Special Issue, entitled “Deep Learning Applications with Practical Measured Results in Electronics Industries”, of *Electronics*. Topics covered in this issue include four main parts: (I) environmental information analyses and predictions, (II) unmanned aerial vehicle (UAV) and object tracking applications, (III) measurement and denoising techniques, and (IV) recommendation systems and education systems. Four papers on environmental information analyses and predictions are as follows: (1) “A Data-Driven Short-Term Forecasting Model for Offshore Wind Speed Prediction Based on Computational Intelligence” by Panapakidis et al.; (2) “Multivariate Temporal Convolutional Network: A Deep Neural Networks Approach for Multivariate Time Series Forecasting” by Wan et al.; (3) “Modeling and Analysis of Adaptive Temperature Compensation for Humidity Sensors” by Xu et al.; (4) “An Image Compression Method for Video Surveillance System in Underground Mines Based on Residual Networks and Discrete Wavelet Transform” by Zhang et al. Three papers on UAV and object tracking applications are as follows: (1) “Trajectory Planning Algorithm of UAV Based on System Positioning Accuracy Constraints” by Zhou et al.; (2) “OTL-Classifer: Towards Imaging Processing for Future Unmanned Overhead Transmission Line Maintenance” by Zhang et al.; (3) “Model Update Strategies about Object Tracking: A State of the Art Review” by Wang et al. Five papers on measurement and denoising techniques are as follows: (1) “Characterization and Correction of the Geometric Errors in Using Confocal Microscope for Extended Topography Measurement. Part I: Models, Algorithms Development and Validation” by Wang et al.; (2) “Characterization and Correction of the Geometric Errors Using a Confocal Microscope for Extended Topography Measurement, Part II: Experimental Study and Uncertainty Evaluation” by Wang et al.; (3) “Deep Transfer HSI Classification Method Based on Information Measure and Optimal Neighborhood Noise Reduction” by Lin et al.; (4) “Quality Assessment of Tire Shearography Images via Ensemble Hybrid Faster Region-Based ConvNets” by Chang et al.; (5) “High-Resolution Image Inpainting Based on Multi-Scale Neural Network” by Sun et al. Two papers on recommendation systems and education systems are as follows: (1) “Deep Learning-Enhanced Framework for Performance Evaluation of a Recommending Interface with Varied Recommendation Position and Intensity Based on Eye-Tracking Equipment Data Processing” by Sulikowski et al. and (2) “Generative Adversarial Network Based Neural Audio Caption Model for Oral Evaluation” by Zhang et al.

Keywords: deep learning; machine learning; supervised learning; unsupervised learning; reinforcement learning; optimization techniques

1. Introduction

Machine learning and deep learning techniques have been the crucial tools when it comes to the feature extracting and event estimating for developing applications in the electronics industries [1–8]. Some techniques have been implemented in the embedded systems and applied to industry 4.0 applications, industrial electronics applications, consumer electronics applications, and other electronics applications. For instance, supervised learning techniques, including neural networks (NN) [9–19], convolutional neural networks (CNN) [20–26], and recurrent neural networks (RNN) [27–32], can be adopted for prediction applications and classification applications in the electronics industries. Unsupervised learning techniques, including restricted Boltzmann machine (RBM) [33,34], deep belief networks (DBN) [35], deep Boltzmann machine (DBM) [36], auto-encoders (AE) [37,38], and denoising auto-encoders (DAE) [39], can be used for denoising and generalization. Furthermore, reinforcement learning techniques, including generative adversarial networks (GANs) [40,41] and deep Q-networks (DQNs) [42], can be used to obtain generative networks and discriminative networks for contesting and optimizing in a zero-sum game framework. These techniques can provide the precise prediction and classification for electronics applications. Therefore, the aim of this Special Issue is to introduce the readers the state-of-the-art research work on deep learning applications with practical measured results in electronics industries.

This Special Issue had received a total of 45 submitted papers with only 14 papers accepted. A high rejection rate of 68.89% of this issue from the review process is to ensure that high-quality papers with significant results are selected and published. The statistics of the Special Issue are presented as follows.

- Submissions (45);
- Publications (14);
- Rejections (31);
- Article types: research article (13); review article (1).

Topics covered in this issue include the following four main parts: (I) environmental information analyses and predictions, (II) unmanned aerial vehicle (UAV) and object tracking applications, (III) measurement and denoising techniques, and (IV) recommendation systems and education systems. Four topics with accepted papers are briefly described below.

2. Environmental Information Analyses and Predictions

Four papers on environmental information analyses and predictions are as follows: (1) “A Data-Driven Short-Term Forecasting Model for Offshore Wind Speed Prediction Based on Computational Intelligence” by Panapakidis et al. [43]; (2) “Multivariate Temporal Convolutional Network: A Deep Neural Networks Approach for Multivariate Time Series Forecasting” by Wan et al. [44]; (3) “Modeling and Analysis of Adaptive Temperature Compensation for Humidity Sensors” by Xu et al. [45]; (4) “An Image Compression Method for Video Surveillance System in Underground Mines Based on Residual Networks and Discrete Wavelet Transform” by Zhang et al. [46].

Panapakidis et al. from Greece and Cyprus in “A Data-Driven Short-Term Forecasting Model for Offshore Wind Speed Prediction Based on Computational Intelligence” considered that the time series data of wind speed has the characters of high nonlinearity and volatilities. Therefore, an adaptive neuro-fuzzy inference system (ANFIS) and a feed-forward neural network (FFNN) were constructed to analyze the nonlinearity and volatilities of wind speed for short-term wind speed prediction. In their experiments, five cases were selected to predict the wind speeds of the 1-min-ahead and 10-min-ahead prediction horizons for the evaluation of the proposed method. The results show that all of mean absolute range normalized errors (MARNEs) of each case by the proposed method were lower than the MARNEs of each case by other methods (e.g., regression neural network, regression trees, support vector regression, etc.) [43].

Wan et al. from China in “Multivariate Temporal Convolutional Network: A Deep Neural Networks Approach for Multivariate Time Series Forecasting” considered that the long-term multivariate dependencies of time series data are hard to be captured. Therefore, a multivariate temporal convolution network (M-TCN) was proposed to combine convolutional layers and residual block for extracting the spatio-temporal features of environmental data. In the experiments, two benchmark datasets including a Beijing PM2.5 dataset and an ISO-NE Dataset were used to compare the M-TCN with other methods for evaluating the proposed method. The results show that the root mean squared errors (RMSEs) of each case by the M-TCN were lower than the RMSEs of each case with other methods (i.e., long short term memory (LSTM), convolutional LSTM (ConvLSTM), Temporal Convolution Network (TCN) and Multivariate Attention LSTM-FCN (MALSTM-FCN)) [44].

Xu et al. from China in “Modeling and Analysis of Adaptive Temperature Compensation for Humidity Sensors” considered that the nonlinear compensation of sensing data is required because the humidity sensitive materials may be sensitive to temperature with nonlinear relationships. Therefore, a genetic simulated annealing algorithm (GSA) was proposed and adopted into a back propagation neural network (BPNN)-based nonlinear compensation model to compensate the sensing data of different temperature ranges. In their experiments, 150 practical datasets were collected by a humidity sensor and used to train the proposed nonlinear compensation model; furthermore, 15 practical datasets were collected and analyzed to test the trained nonlinear compensation model for the performance evaluation of the proposed method. The results show that the errors the proposed method were lower than the errors of other methods (i.e., genetic algorithm-BPNN (GA-BPNN) and artificial fish-swarm algorithm-BPNN (AFSA-BPNN)) [45].

Zhang et al. from China in “An Image Compression Method for Video Surveillance System in Underground Mines Based on Residual Networks and Discrete Wavelet Transform” considered that the image compression can be used to transfer a large number of digital images through lower bandwidth underground channels for the applications of underground mines. Therefore, a neural network containing an encoder module and a decoder module with residual units was constructed, and a metric termed discrete wavelet structural similarity (DW-SSIM) was proposed for the loss function of the neural network. In the experiments, this study collected the images from the COCO 2014 dataset and the images of underground mines for training and testing. The results show that the peak signal-to-noise ratio (PSNR) and the structural similarity (SSIM) of the proposed method were higher than the PSNR and the SSIM of other methods (e.g., denoising-based approximate message passing (D-AMP), ReconNet and total variation augmented Lagrangian alternating direction algorithm (TVAL3)) [46].

3. UAV and Object Tracking Applications

Three papers on UAV and object tracking applications are as follows: (1) “Trajectory Planning Algorithm of UAV Based on System Positioning Accuracy Constraints” by Zhou et al. [47]; (2) “OTL-Classifier: Towards Imaging Processing for Future Unmanned Overhead Transmission Line Maintenance” by Zhang et al. [48]; (3) “Model Update Strategies about Object Tracking: A State of the Art Review” by Wang et al. [49].

Zhou et al. from China in “Trajectory Planning Algorithm of UAV Based on System Positioning Accuracy Constraints” considered that the location information cannot be accurately determined by UAVs with the limitation of system structure. Therefore, this study considered multi-constraints (e.g., vertical errors, horizontal errors, and flight distance) and proposed an improved genetic algorithm and an improved sparse A* algorithm to find the shortest trajectory length. In their experiments, two practical case studies were selected to evaluate the improved genetic algorithm and the improved sparse A* algorithm. The results show that the trajectory length could be reduced by 57.79% by the proposed methods [47].

Zhang et al. from China in “OTL-Classifier: Towards Imaging Processing for Future Unmanned Overhead Transmission Line Maintenance” considered that the transmission line-based robots equipped

with cameras can only travel a line to inspect for maintenance. Therefore, an overhead transmission line classifier based on ResNet (deep residual network) and Faster-RCNN (faster regions with convolutional neural network) was proposed to analyze the images from robots for classification and inspection. In the experiments, 1558 images, which include 406 positive samples and 1152 negative samples, were collected for evaluating the proposed classification method. The results show that the area under curve (AUC) of the proposed classification method was higher than support vector machine (SVM). Furthermore, the precision-recall (PR) curve of the proposed classification method (i.e., ResNet) was also higher than the PR curve of the combination of VGG and Faster-RCNN [48].

Wang et al. from China in “Model Update Strategies about Object Tracking: A State of the Art Review” considered that tracking model update strategies were important factors for the robustness of image recognition. Therefore, the study conducted the literature review of target model update occasions, target model update strategies, and background model updates. Four update strategy types, which include (1) update strategies based on correlation filters, (2) update strategies based on dictionary learning and sparse coding, (3) update strategies based on bag-of-words, and (4) update strategies based on neural network models, were summarized and presented. The experimental results of different update strategies from recent publications were discussed, and it was concluded that the local representation, target re-detection, and background models were important factors for the improvement of object tracking [49].

4. Measurement and Denoising Techniques

Five papers on measurement and denoising techniques are as follows: (1) “Characterization and Correction of the Geometric Errors in Using Confocal Microscope for Extended Topography Measurement. Part I: Models, Algorithms Development and Validation” by Wang et al. [50]; (2) “Characterization and Correction of the Geometric Errors Using a Confocal Microscope for Extended Topography Measurement, Part II: Experimental Study and Uncertainty Evaluation” by Wang et al. [51]; (3) “Deep Transfer HSI Classification Method Based on Information Measure and Optimal Neighborhood Noise Reduction” by Lin et al. [52]; (4) “Quality Assessment of Tire Shearography Images via Ensemble Hybrid Faster Region-Based ConvNets” by Chang et al. [53]; (5) “High-Resolution Image Inpainting Based on Multi-Scale Neural Network” by Sun et al. [54].

Wang et al. from Spain and China in “Characterization and Correction of the Geometric Errors in Using Confocal Microscope for Extended Topography Measurement. Part I: Models, Algorithms Development and Validation” and “Characterization and Correction of the Geometric Errors Using a Confocal Microscope for Extended Topography Measurement, Part II: Experimental Study and Uncertainty Evaluation” considered that the measurement accuracy and error compensation are important issues for measuring machines. Therefore, Wang et al. proposed a mathematical model based on system kinematics for building the scale calibration of the X-coordinate and Y-coordinate in Part I; two experiments were designed based on Monte Carlo method to evaluate the proposed mathematical model and measure different target areas in Part II. In their experiments, 35 cylinders of point cloud were established in a 5×7 area and generated for evaluating the proposed mathematical model. The results show that the mean residuals and squared residuals of the proposed method were higher than those of other methods [50,51].

Lin et al. from China in “Deep Transfer HSI Classification Method Based on Information Measure and Optimal Neighborhood Noise Reduction” considered that high redundant spectral information in the hyperspectral images (HSIs) may interfere with the accuracy of image classification. Therefore, a deep learning method based on a dimensionality reduction method and convolutional neural networks was proposed to improve the accuracy of HIS classification. In the experiments, the dataset of Indian Pines and Salinas which were obtained by Airborne Visible/Infrared Imaging Spectrometer (AVIRIS) sensors were collected for evaluating the proposed method. The results show that the accuracy of the proposed method was higher than that of other methods (e.g., principal component analysis (PCA)) [52].

Chang et al. from Taiwan and India in “Quality Assessment of Tire Shearography Images via Ensemble Hybrid Faster Region-Based ConvNets” considered that the bubble defect detection is an important issue to filter out defective tires for the improvement of driving safety. Therefore, the combination of ensemble convolutional neural network and Faster-RCNN was proposed to detect bubble defects in the shearography images of tires. In their experiments, for the evaluation of the proposed method, 3279 tire images were selected as training data; 797 tire images were selected as testing data. The results show that the accuracy, sensitivity and specificity of the proposed method were higher than those of other methods (e.g., SVM, random forest, Haar-like AdaBoost, etc.) [53].

Sun et al. from China in “High-Resolution Image Inpainting Based on Multi-Scale Neural Network” considered that the blurred textures and the unpleasant boundaries may be obtained by the image inpainting method based on GAN in the cases of high resolution images. Therefore, this study applied the super-resolution using a generative adversarial network (SRGAN) to inpaint image and extract the features of textures for the improvement of image recognition. In the experiments, COCO and VOC datasets which included 135,414 images as training data and 200 images as testing data were selected to evaluate the proposed method. The results show that the PSNR and SSIM of the proposed method were higher than the PSNR and SSIM of other methods [54].

5. Recommendation Systems and Education Systems

Two papers on recommendation systems and education systems are as follows: (1) “Deep Learning-Enhanced Framework for Performance Evaluation of a Recommending Interface with Varied Recommendation Position and Intensity Based on Eye-Tracking Equipment Data Processing” by Sulikowski et al. [55] and (2) “Generative Adversarial Network Based Neural Audio Caption Model for Oral Evaluation” by Zhang et al. [56].

Sulikowski et al. from Poland in “Deep Learning-Enhanced Framework for Performance Evaluation of a Recommending Interface with Varied Recommendation Position and Intensity Based on Eye-Tracking Equipment Data Processing” considered that high correlations may exist between users’ gaze data and interests in human-computer interaction for recommendation inferences. Therefore, this study collected eye-tracking data to train a deep learning neural network model for building an e-commerce recommendation system. In the experiments, 15,922 fixation records were generated by eye-tracking devices from 52 participants. The results show that the accuracies of training dataset and testing dataset were 98.4% and 98.2%, respectively [55].

Zhang et al. from China in “Generative Adversarial Network Based Neural Audio Caption Model for Oral Evaluation” considered that the massive human work is required by oral evaluation for testing children’s language learning. Therefore, an automated expert comment generation method based on gated recurrent units (GRUs), LSTM networks and GANs was proposed to extract the features of orals and generate expert comments. In their experiments, the proposed neural audio caption model (NACM) and the proposed GAN-based NACM (GNACM) were implemented and compared; several oral audios from the children of 5-6 years old were collected for evaluating the proposed models. The results show that scores of GNACM were higher than the scores of NACM; furthermore, the average response time of GNACM was lower than that of NACM [56].

6. Conclusions and Future Work

Four main parts, including (I) environmental information analyses and predictions, (II) UAV and object tracking applications, (III) measurement and denoising techniques, and (IV) recommendation systems and education systems, are collected and discussed in this Special Issue. These articles utilized and improved the deep learning techniques (e.g., ResNet, Fast-RCNN, LSTM, ConvLSTM, GAN, etc.) to analyze and denoise measured data in a variety of applications and services (e.g., wind speed prediction, air quality prediction, underground mine applications, neural audio caption, etc.). Several practical experiments were given in these articles, and the results indicated that the performance of

the improved deep learning methods could be higher than the performance of conventional machine learning methods [43–56].

In the future, the federated learning techniques can be considered to train deep learning and machine learning models across multiple decentralized servers for data privacy and data security in electronics industries. Furthermore, the optimization techniques (e.g., gradient descent algorithm, Adam optimization algorithm, particle swarm optimization algorithm [57,58], etc.) can be improved for finding the global optimal solution.

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