Talent Education for Deep Learning-based Automated Optical Inspection

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***Abstract*—Automated Optical Inspection (AOI) systems majorly work for electronics and semiconductor manufacturing industry. They are useful in improving the quality and performance of the production lines, along with enhancement in inspection speed. In recent years, rapid development of deep learning technologies had changed the face of the industry. In order to master new AOI skills, cultivating AI talent is an urgent task around the world. Here we introduced the development of an AOI curriculum and reported the learning outcome from a group of undergraduate students. The lesson plan is available for the industry to train high-caliber talents of AOI expertise.**

Keywords- cultivation of AI talent; Automated Optical Inspection; deep learning

I. INTRODUCTION *(HEADING 1)*

Almost all of big countries around the world have ramped investment in artificial intelligence for various applications such as transportation, banking, healthcare and manufacturing. There are many companies making essential investments in AI-powered approaches to improve different aspects of manufacturing[1]. For an example, intelligent predictive maintenance can estimate the condition of in-service equipment and determine when to perform maintenance before potential disaster disorder event. Besides, defect detection is a more common problem. Not only electronics industry but also other industries such as textile industry hires massive workers for checking defects [2]. In consequence, automation of defect detection will reduce labor costs. For manufacturers, it is an urgent need how to master deep learning-based AOI technology.

In addition, from the perspective of education, how to cultivate AI talents in line with industrial needs is an important issue as well [3, 4]. We believe that hands-on courses with real industrial data are important for the purpose. Consequently, we developed an AOI learning course with the AIdea platform (https://aidea-web.tw) provided by Industrial Technology Research Institute of Taiwan (ITRI). The AIdea platform is supported by Department of Industrial Technology of the Ministry of Economic Affairs, Taiwan. Its original purpose is to play the role of bridging the industry and the academia. From 2018, the AIdea platform provided the functionality for teachers to plan a course project with the real industrial datasets. However, before the challenge of an AIdea course project such as the AOI project, it is necessary for students to receive sufficient program skills and machine learning knowledge. On the contrary, there are too many open machine learning courses available through the Internet and it's difficult for a student to choose proper learning materials to deal with real AOI problems. Consequently, we provides this AOI courseware within a repository of Github[1].

II. THE AOI DATASET

The AOI dataset on the AIdea platform is composed of 12,670 images of resolution 512x512 collected from the coating process of flexible electronic displays. These images were labeled into six classes. The images of class (a) are normal, and those of the other five classes are with different types of flaws: class (b) is void; class (c) is with horizontal defect; class (d) is with vertical defect; class (e) is with edge defect; class (f) is with particle (Fig. 1). They are spitted into a training set of 2,528 images and a test set of 10,142 images. Figure 2 shows the numbers of images of different classes in the training set. The AOI problem is a typical supervised multi-class classification problem (Fig. 3).

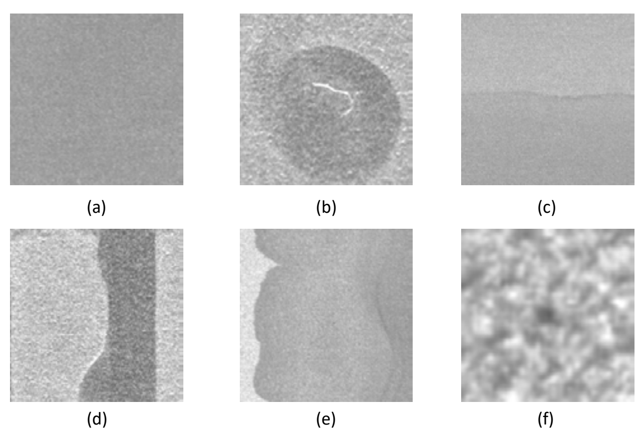

Figure 1. The six classes of AOI images: (a) normal, (b) void; (c) horizontal defect; (d) vertical defect; (e) edge defect; (f) particle.

[1] https://github.com/htchu/TalentTrainingAOI

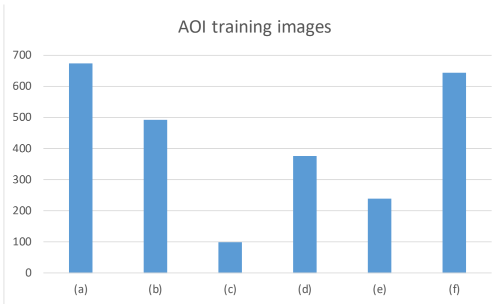

Figure 2. the numbers of images of different classes in the training set of the AOI problem.

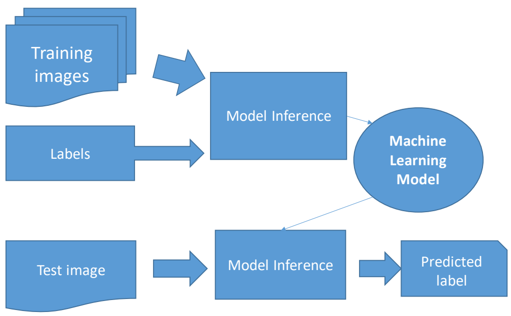

Figure 3. The AOI problem as a typical supervised machine learning model.

III. Course Composition

A. *Structure of the proposed AOI curriculum*

The proposed AOI curriculum contains nine subjects listed in Table 1. We suggest each subject can be taught in 3-9 hours and totally in 27-54 hours. However, it is optional if the students had the background of Python programming or machine learning. The full modules are for learning AOI from scratch. The first eight subjects can be practiced with online jupyter notebooks, e.g., Google Colaboratory (Colab) or Microsoft Azure Notebooks. The last subject will deal with entire AOI dataset (1.67G) and then it is better to run the programs on local computer. The most convenient way is to install the Anaconda package which can easily set up GPU-enable computation environment for training deep learning models.

Table 1: Learning subjects of the proposed AOI curriculum

Subjects	hours	Platform
Python basics	3-9 hours	Colab/Azure
NumPy	3 hours	Colab/Azure
Matplotlib	3-6 hours	Colab/Azure
Pandas	3-6 hours	Colab/Azure
ScikitImage	3-6 hours	Colab/Azure
ScikitLearn	3-6 hours	Colab/Azure
TensorFlow and Keras	3-6 hours	Colab/Azure
CNN for AOI	3-6 hours	Colab/Azure
AOI pipeline	3-6 hours	Anaconda

B. *Basic Python programming*

Python is an interpreted programming language with rich data structures and a big standard library. Besides, there are numerous third-party libraries for different applications. In the module of basic Python programming, we introduce the basics of the Python language including syntax, data types, functions, expressions, libraries.

C. *Data manipulation and visualization*

The subjects 2-4 are for data manipulation and visualization. The library NumPy defines the ndarray class which provides the fast operations on arrays, including mathematical, logical, shape manipulation, sorting, selecting, I/O, linear algebra, random simulation and much more. The Matplotlib is a popular plotting library. Using Jupyter Notebook, the command "%matplotlib inline" will enable the display of plotting commands directly below the code cell that produced it and the output plots will then also be stored in the notebook document.

The pandas library is for data I/O and analysis with two powerful data structure types Series and DataFrame. With the pandas library, it is easy to import any format of data files such as txt, csv, tsv, HDF5 and excel xlsx or to read/write data from different SQL databases. Then, there are many data manipulation functions working on DataFrame objects: aggregation, transformation, filtering, indexing, selecting and plotting. The three libraries (NumPy, Matplotlib and Pandas) are important for learning data analytics using Python.

D. *Image processing*

There are a lot of Python libraries which can read/write image files, including imageio, PIL/Pillow, OpenCV, SimpleCV, Mahotas, SimpleITK, pgmagick, Pycairo and scikit-image. Besides, the libraries NumPy and SciPy also contain image IO and processing functions. The usage of image libraries is very diverse in different solutions.

In recent Python programming, Python Imaging Library (PIL) and Open Source Computer Vision (OpenCV) are two libraries frequently used for image processing. However, scikit-image is a newer library with a collection of algorithms for visual features such as histogram of oriented gradients (HOG) [5] and scale-invariant center-surround detector (CENSURE) [6]. As a result, we chose ScikitImage in the subjects for learning AOI. However, we still have kept some alternative modules using PIL and OpenCV.

E. *Machine learning and deep learning*

Scikit-learn is the key library for machine learning in Python [7]. It is designed to interoperate with NumPy and SciPy for providing various classification, regression and clustering algorithms. For example, the function train_test_split() can split arrays or matrices into random train and test subsets.

For students to quickly learn deep learning to make accurate predictions of AOI images, we adapted the approach of Transfer Learning [8] with the VGG16 model. The VGG16 model is a convolutional neural network model submitted to ILSVRC-2014 for the classification of ImageNet images [9]. Figure 3 shows the structure of the VGG16 model combined of convolution layers, pooling layers and dense layers. Using Transfer Learning means we don't train all of the parameters of the neural network model for saving computation time. In this case, we preserve all of the parameters of convolution and pooling layers. And just rebuild the dense (fully connected) layers by training the model with the AOI images.

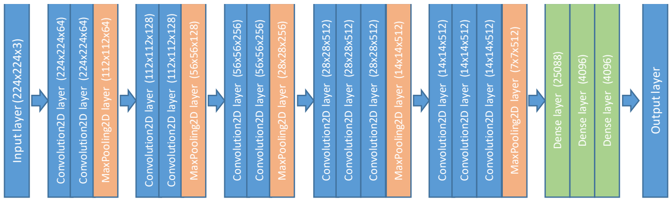

Figure 4. the network structure of the VGG16 model.

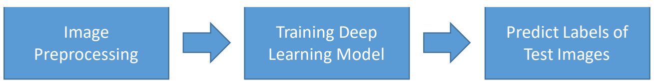

Figure 5. the AOI pipeline.

F. *AOI pipeline*

The last learning module is to deal with the real images in the AOI dataset. We divided the whole process of AOI system into three modules: preprocessing, training model and inference the labels of the test images. In the preprocessing step, we resize the original images from 512x512 to 224x224 for reusing the first layers of the VGG model. Then we train and save the customized VGG model into HDF format. The last step is to restore the model and use it to predict the labels of test images.

IV. LEARNING OUTCOME

We implemented this AOI course for university students. 90% of the students are second-year, the others are third-year. Most students don't have the background of machine learning and deep learning. Even, it was the first time for them to learn course in Python.

A. *Participation of AIdea project*

All of the students got an account of the AIdea platform (https://aidea-web.tw/). 84% students finished the AOI project. For reaching better accuracy, the students had to try different ImageNet models by themselves such as ResNet [10] and Inception [11]. Table 2 list the top results of AOI predictions by the students. The best result reaches 99.36% accuracy by a student who learned machine learning for the first time.

Table 2: the top 5 results of AOI predictions

Ranking	Accuracy
1	0.9936
2	0.9896
3	0.9859
4	0.9684
5	0.9652

Figure 6. Example of a TWO-COLUMN figure caption: (a) this is the format for referencing parts of a figure.

B. *Learning effectiveness*

Figure 7 is a comparison about the students knew the AOI problem before and after the class. More than 86% students approved that they knew better to solve the AOI problem. Moreover, the AOI project also helped them to understand the concept of AI topics: Data Science and Deep Learning (Fig. 8).

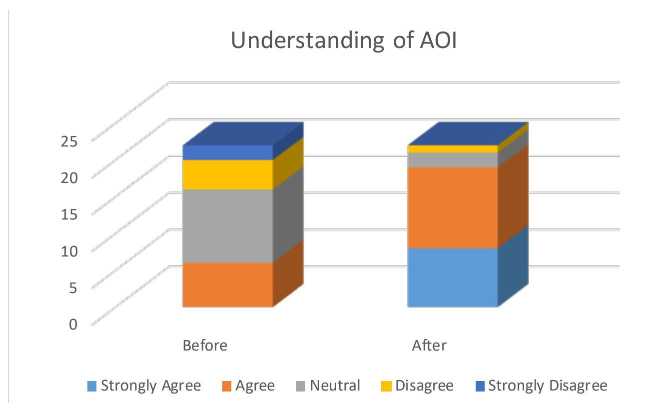

Figure 7. The level of understanding of the AOI topic before and after class.

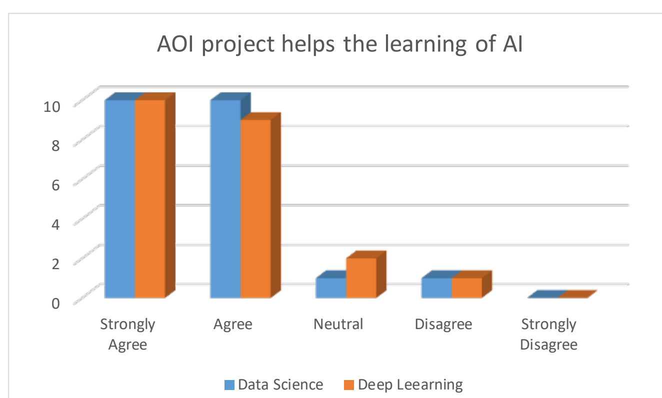

Figure 8. The AOI project helps the students to learn the two topics of AI: Data Science and Deep Learning.

V. CONCLUSION AND FUTURE WORKS

Traditional automated Optical Inspection (AOI) systems [12] face two problems: overkill and underkill. The overkill problem is an AOI system reject an object that's actually good. The underkill problem is an AOI system cannot find a bad object. To reduce both overkill and underkill problem, deep convolutional neural networks have been shown to perform better inspection to yield better accuracy [13, 14]. We introduce an analytic course to cultivating AI talent for meeting the need of building modern AOI systems.

The effectiveness of a deep learning model depends on massive training data. The AIdea platform provides well-labeled datasets from real industrial or social sources. Therefore, these datasets are good material for students to learn the real AI applications. In this paper, we report our course using the AOI dataset on the AIdea platform. In the future, we will develop more courses for AI talent education on the AIdea platform

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REFERENCES

[1] française, V.l.v. Global AI Talent Report 2019. 2019; Available from: https://jfgagne.ai/talent-2019/.

[2] Yapi, D., et al., A Learning-Based Approach for Automatic Defect Detection in Textile Images. IFAC-PapersOnLine, 2015. 48(3): p. 2423-2428.

[3] Han, X., et al. Design of AI + Curriculum for Primary and Secondary Schools in Qingdao. in 2018 Chinese Automation Congress (CAC). 2018.

[4] Kay, J., AI and Education: Grand Challenges. IEEE Intelligent Systems, 2012. 27(5): p. 66-69.

[5] Dalal, N. and B. Triggs. Histograms of oriented gradients for human detection. 2005.

[6] Agrawal, M., K. Konolige, and M. Blas, CenSurE: Center Surround Extremas for Realtime Feature Detection and Matching. Vol. 5305. 2008. 102-115.

[7] Pedregosa, F., et al., Scikit-learn: Machine learning in Python. Journal of machine learning research, 2011. 12(Oct): p. 2825-2830.

[8] Pan, S.J. and Q. Yang, A survey on transfer learning. IEEE Transactions on knowledge and data engineering, 2009. 22(10): p. 1345-1359.

[9] Simonyan, K. and A. Zisserman, Very deep convolutional networks for large-scale image recognition. arXiv preprint arXiv:1409.1556, 2014.

[10] He, K., et al. Deep residual learning for image recognition. in Proceedings of the IEEE conference on computer vision and pattern recognition. 2016.

[11] Szegedy, C., et al. Inception-v4, inception-resnet and the impact of residual connections on learning. in Thirty-First AAAI Conference on Artificial Intelligence. 2017.

[12] Li, W. and D. Tsai, Defect Inspection in Low-Contrast LCD Images Using Hough Transform-Based Nonstationary Line Detection. IEEE Transactions on Industrial Informatics, 2011. 7(1): p. 136-147.

[13] Konrad, T., L. Lohmann, and D. Abell. Surface Defect Detection for Automated Inspection Systems using Convolutional Neural Networks. in 2019 27th Mediterranean Conference on Control and Automation (MED). 2019.

[14] Parakontan, T. and W. Sawangsri. Development of the Machine Vision System for Automated Inspection of Printed Circuit Board Assembl. in 2019 3rd International Conference on Robotics and Automation Sciences (ICRAS). 2019.