An Innovative Table Tennis Scoring System Using Deep Residual Network

Yu-Huei Cheng, *Member, IAENG*, Duc-Man Nguyen, and Che-Nan Kuo

Abstract—**The rise of various sports in recent years has made more and more people pay attention to the referee's judgment. Not only the players themselves, but also the fans will pay attention to the verdict. Fans don't want players or teams they support to lose due to referee's bias. World-class competition must emphasize fairness and justice. However, because of the subjective consciousness or negligence of the referee, it may lead to wrong judgment. This study proposes an innovative table tennis scoring system using deep residual network based on classified data and the deep learning technology. The aim is to improve the judgment of subjective consciousness and negligence, so as to score the table tennis competition through intelligence and automation. This study is mainly divided into three major steps in practice. The first step is collecting image data, including table tennis table, table tennis balls, people, background, etc., as training images, verification images, and test videos. The second step is training a reliable deep learning model, by using deep learning to infer the scoring situation of the table tennis competition. The third step is to use the embedded system integrated camera as the image monitoring of the table tennis competition, and combine the trained deep learning model with the microcontroller unit to control the scoring display to display the immediate score result.**

Index Terms—**Table tennis; scoring system; deep residual network; deep learning.**

I. Introduction

THE rise of various sports in recent years has made more and more people pay attention to the referee's judgment. Not only the players themselves, but also the fans will pay attention to the verdict. Fans don't want players or teams they support to lose due to referee's bias. World-class competition must emphasize fairness and justice. However, because of the subjective consciousness or negligence of the referee, it may lead to wrong judgment. Table tennis is a ball game that is popular in many parts of the world. Players from both sides played against each other across a table with a net. It can be divided into singles or doubles, the two sides hit each other until one cannot return the ball and the other can score easily. Table tennis developed from tennis and originated in England at the end of the 19th century. Europeans love tennis, but because of the limitations of venues and weather, they moved tennis indoors, using the dining table as the venue, and slowly developed the game of billiards. Table tennis is also known as "Indoor tennis". In the early 20th century, table tennis flourished in Europe and Asia. In 1926, the World Table Tennis Championships was held in Berlin, Germany, and the International Table Tennis Federation (ITTF) [1] was established at the same time.

The rise of artificial intelligence (AI) has addressed many of the common cognitive problems associated with human intelligence, such as learning, problem solving, and pattern recognition. In particular, deep learning uses artificial neural networks to enable digital systems to learn and make decisions based on unstructured, unlabeled data. The advent of deep learning has brought the AI field to another peak. In recent years, many researchers have applied deep learning to solve many problems. In 2018, Wang *et al.* propose a novel deep learning-based interactive segmentation framework by incorporating CNNs into a bounding box and scribble-based segmentation pipeline for automatic medical image segmentation [2]. In 2019, Kim *et al.* proposes an algorithm to collect training data from a driving game for to drive real world children's car [3]. In 2020, Zhang *et al.* propose deep learning, ray tracing algorithm, waiting rule, and rapidly-exploring random tree to solve the problem of obstacle avoidance and path planning [4]. In 2021, Cheng *et al.* propose CRNN (Convolutional Neural Networks combined with Recurrent Neural Network) for music genre classification [5]. In 2022, Cheng *et al.* use YOLOv4 deep-learning framework to grade cherry tomatoes and their experimental results is amazing for getting approximately 99.9% accurate [6]. Many cases can be found in the literature.

In the past, many studies related to table tennis are presented. In 2005, Matsushima *et al.* propose a method for controlling a table tennis robot to return an incoming ball to a desired point on the table within a specified flight duration. They also propose a feedforward control scheme based on iterative learning control to accurately achieve the stroke motion of the paddle determined by using the developed maps. Their experimental results including rallies with human adversaries are also reported to demonstrate the effectiveness of their approach [7]. In 2013, Renò, V., *et al.* propose a framework that allows robots to learn cooperative table tennis through physical interaction with humans. They let the robot first learn a set of basic table tennis hitting movements from a human table tennis teacher through kinesthetic teaching, and compile it into a set of motion primitives represented by the dynamic system. Subsequently, the robots generalized these motions to a wider range of

Manuscript received March 3, 2022; revised December 19, 2022. This work was supported in part by the National Science and Technology Council (NSTC) in Taiwan under grant no. 111-2622-E-324-004, 111-2221-E-432-001, 111-2821-C-324-001-ES, and 111-2218-E-005-009.

Y.-H. Cheng is a distinguished professor of the Department of Information and Communication Engineering, Chaoyang University of Technology, Taichung 413310, Taiwan (e-mail: yuhuei.cheng@gmail.com).

D.-M. Nguyen is a dean of the International School, Duy Tan University, 254 Nguyen Van Linh, Danang, Vietnam (e-mail: mannd@duytan.edu.vn).

C.-N. Kuo is an associate professor of the Department of Artificial Intelligence, CTBC Financial Management College, Tainan 709, Taiwan (corresponding author. e-mail: fkikimo@hotmail.com).

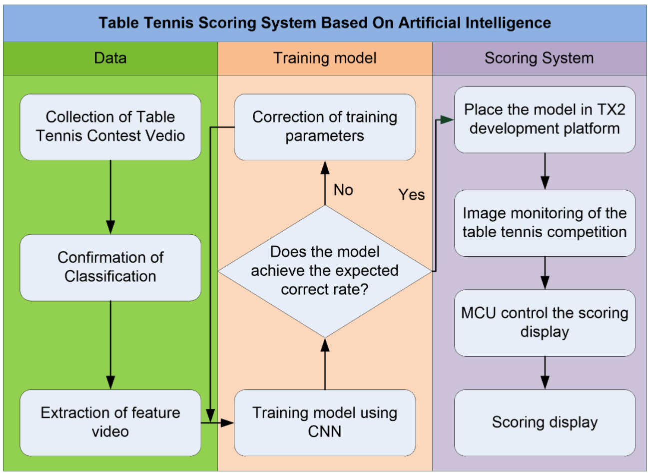

Fig. 1. The system architecture diagram of the scoring system for table tennis based on artificial intelligence.

situations using their motion primitive hybrid approach [8]. In 2013, Mülling, K., *et al.* studied human movement during table tennis and demonstrated a robotic system that mimics human hitting behavior. Their focus is on producing shots that can adapt to changing environmental conditions. Therefore, they modeled the human motion involved in hitting a table tennis ball using discrete motion phases and virtual hitting point assumptions [9]. Furthermore, many table tennis-related studies have been proposed [10-13]. In recent years, artificial intelligence [14] has been applied to various fields of life, such as industry [15, 16], family [17], medical [18, 19], education [20], finance [21], sports [22], criminal cases forecasting [23], residential building energy efficiency performance [24] etc. Almost all kinds of applications appear the traces of artificial intelligence. Certain machine learning methods have also been imported into table tennis research. Muelling, K., *et al.* propose a computational model for representing and inferring policies based on Markov decision problems, showing how model-free inverse reinforcement learning can be used to discover reward functions from demonstrations of table tennis matches to model task objectives and strategic information [25]. Tabrizi, S. S., *et al.* conduct a comparative study considering support vector machines (SVMs) with radial basis function (RBF) kernel functions, long short-term memory (LSTM), and two-dimensional convolutional neural networks (2D-CNN) to examine ping pong balls Forehand classification of three machine learning (ML) models [26]. We propose a deep residual network for perform table tennis scoring based AI embedded platform in this study.

II. Methods

This study uses NVIDIA Jetson TX2 and Arduino Pro Mini to achieve a scoring system for table tennis based on artificial intelligence. In terms of research processes, we first collect and process a large amount of data for table tennis competitions at the beginning, including using video to capture fragments and images to classify various scores. Then 75% of the data collected and processed for a large number of table tennis competitions are sent to CNN (Convolutional Neural Network) [8] for machine learning. After the data training is completed, we get a model and use the remaining 25% of the data for model testing to confirm the accuracy of the model. If the model does not reach the expected accuracy rate, we check whether the data needs to be revised and amended the algorithm parameters, and then re-train to achieve a higher and expected model accuracy rate, and put it into NVIDIA Jetson TX2 for actual identification. Next, this study used the Arduino Pro Mini to develop the scoring display control circuit and combined it with the NVIDIA Jetson TX2 to transmit the score signal calculated by the NVIDIA Jetson TX2 to the Arduino Pro Mini scoring device to display the score results of both parties. Fig. 1 is the system architecture diagram of this study.

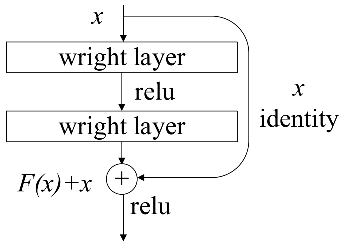

Fig. 2. ResNet residual network.

This proposed method mainly uses ResNet [9, 10]. The following briefly introduces this neural network. ResNet achieves deeper training by adding layers. In the past, deep learning will increase the error rate due to the increase of layer and overtraining, while ResNet uses residual learning to reduce the error rate. The so-called residual learning is shown in Fig. 2.

In the past, learning is to input data and then identify features, while residual learning is the input is the last input plus the residual, that is, more identity. When nothing is learned this time, the residual is zero. When the residual is 0, the input remains the original input. At this time, this layer is called equal mapping. That is to say, even if the new layer is not learned, the model will not degenerate. In fact, the residual will not be exactly equal to 0, so multiple layers can be added. Each layer can learn new complex features. Fig. 3 is the ResNet architecture diagram, and Fig. 4 is the actual

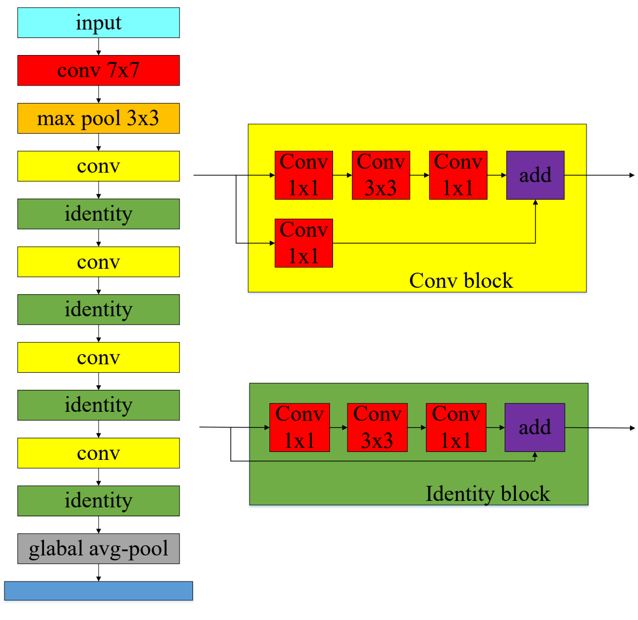

Fig. 3. ResNet actual architecture diagram.

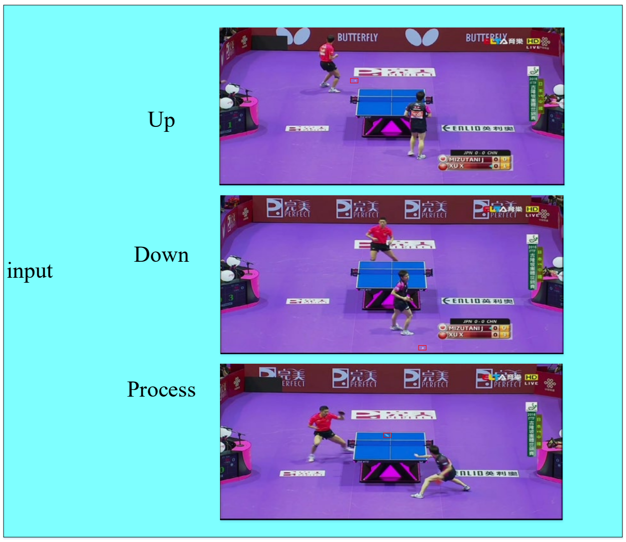

Fig. 4. Actual data input.
(These images are captured from the actual table tennis competitions)

data input situation. We divide it into three categories: Up, Down, and Process. The label "Up" means that scored by the upper player; the label "Down" means that scored by the lower player; the label "Process" means that both players are hitting.

2.1 System environment

The system environment used in this study is divided into two parts: hardware and software. The software includes Python-3.7.6, Tesorflow-gpu-2.1.0, Keras-2.1.6, CNN (ResNet), and Ubuntu18.04; hardware includes artificial intelligence workstation, NVDIA Jetson TX2 development board, Arduino development board, 500 Megapixel camera module, and seven-segment display.

2.2 Research methods and procedures

The method and steps of this study are as follows:

Step 1: Collect information

First, we grab the table tennis competitions video from the Internet, and edit the video into a scored round, then cut multiple pictures of the video, and classify the video according to the score of the original video, which is divided into three categories: "UP", "Down", and "Process". In order to avoid errors due to the file name of the data during training, a Python program was written to name the data in order of numbers, each with 600 sheets for each category, a total of 1,800 sheets.

Step 2: Use ResNet for training to train the model

ResNet is a deep learning algorithm that is mostly used for image recognition. We apply it to a video composed of multiple consecutive images, put the classified images into ResNet according to their situation, and then train the output model through artificial intelligence workstations.

Step 3: Put the model into NVIDIA Jetson TX2

In this study, NVIDIA Jetson TX2 is selected to determine the position of the ball moving at high speed, and is used to analyze the scoring conditions. NVIDIA Jetson TX2 is a high-performance edge-side artificial intelligence computing device that contributes to the development of this study. If other development boards are used, such as NVIDIA Jetson Nano, there may be a delay problem. Table I lists the comparison of NVIDIA Jetson TX2, NVIDIA Jetson Nano, and Raspberry pi 4 development board specifications.

TABLE I
COMPARISON OF HOME CONTROLLERS FOR PLC, ARDUINO, AND RASPBERRY PI

Controller / Specifications	NVIDIA Jetson TX2	NVIDIA Jetson Nano	Raspberry Pi 4
CPU	No need to transfer voltage when connecting home appliances	Booster module is needed for connecting home appliances	Booster module is needed for connecting home appliances
GPU	Excellent	Worse	Good
Memory	Write 100,000 times	Write/clear 100,000 times	Save 100,000 times

If high-speed recognition is required in deep learning, it must have strong parallel computing capabilities, so a GPU with a CUDA core must be selected. Therefore, Raspberry Pi 4 is not the first choice, and the NVIDIA Jetson TX2 development board with CUDA technology was chosen. NVIDIA Jetson TX2 has 128 more CUDA cores than NVIDIA Jetson Nano, which is more efficient than NVIDIA Jetson Nano in terms of computing.

Step 4: Set up the camera on NVIDIA Jetson TX2 and adjust the shooting angle

The camera of the development board should be placed at the same height position as the camera when collecting data, if there is a deviation, it will cause the model to judge the error. Because this study uses the table as the x-axis and the net as the y-axis, the camera is the origin. Therefore, inappropriate position of the camera will make the image have a three-dimensional effect and it is impossible to use the plan view to judge the score.

Step 5: Connect NVIDIA Jetson TX2 and Arduino

The scoring signal is transmitted from NVIDIA Jetson TX2 to Arduino Pro Mini to make the numbers of the seven-segment display count up.

III. RESULTS

The results of model training are shown in Fig. 5 and Fig. 6. Table II shows the loss, accuracy, validation loss, and validation accuracy obtained in each epoch; Table III shows the accuracy rate, recall rate, and comprehensive classification rate of each category.

From the results, validation loss did not decrease steadily. The reason for this situation may be that the characteristics of this dataset are not obvious enough, causing the three categories to be misjudged as images of other conditions. Furthermore, there is no way to identify whether the ball has landed in the image taken with the eagle eye, so even if it is flying in the air, it will be regarded as a scoring signal. This leads to a high return rate of a certain category, which makes

Fig. 5. Scored by the upper player.
(This figure is captured from competition on network)

Fig. 6. Scored by the lower player.
(This figure is captured from competition on network)

it impossible to correctly identify the whole. In terms of video, because the different venues of each competition in the network data, the floor has a color similar to that of table tennis, which leads to a blind spot in the data that overlaps with the color of the venue in some situations. In addition, the Hawkeye system is based on unilateral oblique shooting, and one side of the field will be wider, resulting in non-equal datasets. During the test, we found that even if the amount of data in each category is the same, there will still be categories that will not be recognized during identification. The main reason may be that our information is still insufficient and we need all the images of the sphere at any position on the court. Furthermore, our classification will have the same situation no matter how it is divided, and it will be replaced by other features during training. In addition, the spherical features are not obvious.

IV. Conclusion

The purpose of this study is to use artificial intelligence technology to improve the fairness of current competition judgments. Although there are still many blind spots in the judgment, such as the player's body blocking the camera and the sphere is not obvious, the proposed method can be used as a reference for future AI scoring technology. In the future, we will improve related issues by setting up multi-faceted cameras, and pre-emphasize the sphere using image processing methods to make the sphere more obvious, so as to improve the accuracy of the algorithm.

TABLE II
Loss, accuracy, validation loss, and validation accuracy obtained in each epoch

Epoch	Loss	Accuracy	Validation loss	Validation accuracy
1	1.2747	0.3699	1.0367	0.3235
20	0.6001	0.7584	0.8452	0.5845
40	0.4734	0.8095	1.0062	0.5612
60	0.4209	0.8400	1.0159	0.4544
80	0.3959	0.8370	1.3164	0.4485
100	0.3796	0.8524	0.7454	0.6078
120	0.3490	0.8755	1.3505	0.4951
140	0.3253	0.8717	1.3992	0.4544
150	0.3182	0.8842	1.2749	0.4000

TABLE III
Loss, accuracy, validation loss, and validation accuracy obtained in each epoch

Category	Precision	Recall	F1-score	Support
down	1.00	0.09	0.16	182
process	0.86	0.13	0.23	183
up	0.36	0.99	0.53	182
down	1.00	0.09	0.16	182

References

[1] "International Table Tennis Federation." https://www.ittf.com/ (accessed 2022/03/11).
[2] G. Wang *et al.*, "Interactive medical image segmentation using deep learning with image-specific fine tuning," *IEEE transactions on medical imaging,* vol. 37, no. 7, pp. 1562-1573, 2018.
[3] J. Kim, G. Lim, Y. Kim, B. Kim, and C. Bae, "Deep learning algorithm using virtual environment data for self-driving car," in *2019 International Conference on Artificial Intelligence in Information and Communication (ICAIIC)*, 2019: IEEE, pp. 444-448.
[4] L. Zhang, Y. Zhang, and Y. Li, "Path planning for indoor mobile robot based on deep learning," *Optik,* vol. 219, p. 165096, 2020.
[5] Y.-H. Cheng, P.-C. Chang, D.-M. Nguyen, and C.-N. Kuo, "Automatic Music Genre Classification Based on CRNN," *Engineering Letters,* vol. 29, no. 1, pp. 312-316, 2020.
[6] Y.-H. Cheng, C.-Y. Tseng, D.-M. Nguyen, and Y.-D. Lin, "YOLOv4-Driven Appearance Grading Filing Mechanism: Toward a High-Accuracy Tomato Grading Model through a Deep-Learning Framework," *Mathematics,* vol. 10, no. 18, p. 3398, 2022.
[7] M. Matsushima, T. Hashimoto, M. Takeuchi, and F. Miyazaki, "A learning approach to robotic table tennis," *IEEE Transactions on robotics,* vol. 21, no. 4, pp. 767-771, 2005.
[8] V. Renò *et al.*, "A technology platform for automatic high-level tennis game analysis," *Computer Vision and Image Understanding,* vol. 159, pp. 164-175, 2017.
[9] K. Mülling, J. Kober, O. Kroemer, and J. Peters, "Learning to select and generalize striking movements in robot table tennis," *The International Journal of Robotics Research,* vol. 32, no. 3, pp. 263-279, 2013.
[10] M. Pfeiffer, H. Zhang, and A. Hohmann, "A Markov chain model of elite table tennis competition," *International Journal of Sports Science & Coaching,* vol. 5, no. 2, pp. 205-222, 2010.
[11] K. Muelling, J. Kober, and J. Peters, "Learning table tennis with a mixture of motor primitives," in *2010 10th IEEE-RAS International Conference on Humanoid Robots*, 2010: IEEE, pp. 411-416.
[12] Z. Zhang, D. Xu, and M. Tan, "Visual measurement and prediction of ball trajectory for table tennis robot," *IEEE Transactions on Instrumentation and Measurement,* vol. 59, no. 12, pp. 3195-3205, 2010.
[13] G. Brunnett, S. Rusdorf, and M. Lorenz, "V-Pong: an immersive table tennis simulation," *IEEE Computer Graphics and Applications,* vol. 26, no. 4, pp. 10-13, 2006.
[14] P. H. Winston, *Artificial intelligence*. Addison-Wesley Longman Publishing Co., Inc., 1992.

[15] J. Lee, H. Davari, J. Singh, and V. Pandhare, "Industrial Artificial Intelligence for industry 4.0-based manufacturing systems," *Manufacturing letters,* vol. 18, pp. 20-23, 2018.

[16] M. Jimenez-Martinez and M. Alfaro-Ponce, "Fatigue Life Prediction of Aluminum Using Artificial Neural Network," *Engineering Letters,* vol. 29, no. 2, pp. 704-709, 2021.

[17] W. Liaw and I. Kakadiaris, "Artificial intelligence and family medicine: better together," *Family Medicine,* vol. 52, no. 1, pp. 8-10, 2020.

[18] K.-H. Yu and I. S. Kohane, "Framing the challenges of artificial intelligence in medicine," *BMJ quality & safety,* vol. 28, no. 3, pp. 238-241, 2019.

[19] D. Li, D. Yang, J. Zhang, and X. Zhang, "Ar-ann: Incorporating association rule mining in artificial neural network for thyroid disease knowledge discovery and diagnosis," *IAENG International Journal of Computer Science,* vol. 47, no. 1, pp. 25-36, 2020.

[20] D. McArthur, M. Lewis, and M. Bishary, "The roles of artificial intelligence in education: current progress and future prospects," *Journal of Educational Technology,* vol. 1, no. 4, pp. 42-80, 2005.

[21] C. Dunis, P. Middleton, A. Karathanasopolous, and K. Theofilatos, *Artificial intelligence in financial markets*. Springer, 2016.

[22] L. Xian, "Artificial intelligence and modern sports education technology," in *2010 International Conference on Artificial Intelligence and Education (ICAIE)*, 2010: IEEE, pp. 772-776.

[23] W. Wongsinlatam and S. Buchitchon, "Criminal cases forecasting model using a new intelligent hybrid artificial neural network with cuckoo search algorithm," *IAENG International Journal of Computer Science,* vol. 47, no. 3, pp. 481-490, 2020.

[24] M. Irfan, F. Ramlie, M. L. Widianto, and A. Faruq, "Prediction of Residential Building Energy Efficiency Performance using Deep Neural Network," *IAENG International Journal of Computer Science,* vol. 48, no. 3, pp. 731-737, 2021.

[25] K. Muelling, A. Boularias, B. Mohler, B. Schölkopf, and J. Peters, "Learning strategies in table tennis using inverse reinforcement learning," *Biological cybernetics,* vol. 108, no. 5, pp. 603-619, 2014.

[26] S. S. Tabrizi, S. Pashazadeh, and V. Javani, "Comparative study of table tennis forehand strokes classification using deep learning and SVM," *IEEE Sensors Journal,* vol. 20, no. 22, pp. 13552-13561, 2020.

Yu-Huei Cheng (M'12) received the M.S. degree and Ph.D. degree from the Department of Electronic Engineering, National Kaohsiung University of Applied Sciences, Taiwan, in 2006 and 2010, respectively. He has a lot of experience in the design and development of information and communication engineering projects. He is currently a distinguished professor of Department of Information and Communication Engineering, Chaoyang University of Technology, Taichung, Taiwan. his research interests include artificial intelligence and internet of things, embedded systems, evolutionary computation, intelligent computation, intelligent control, machine learning, mobile medical, smart healthcare, and unmanned vehicle. He can be reached by email: yuhuei.cheng@gmail.com.

Duc-Man Nguyen received his B.S. degree in the Duy Tan University, Danang, Vietnam in 1999, the M.S. degree in the Da Nang University of Technology, Vietnam in 2009, and Ph.D. degree from the Duy Tan University, Da Nang, Vietnam in 2020. Now, he is a Dean of International School, Duy Tan University. His current research interests include software engineering, software testing and automation, software architecture and design, database and database management systems, database integration/ exchange, software/system project management, agile development and testing.

Che-Nan Kuo received the B.S. degree in the Department of Computer Science from the Tunghai University, Taichung, Taiwan in 2002, and the M.S. and Ph.D. degrees from the Department of Computer Science and Information Engineering at the National Cheng Kung University, Tainan, Taiwan in 2004 and 2009, respectively. Now, he is an Associate Professor in the Department of Artificial Intelligence, CTBC Financial Management College, Tainan, Taiwan. He has many excellent research papers about fault-tolerant computing which have been published on some famous journals, such as Theoretical Computer Science, Discrete Applied Mathematics, Information Sciences, and Computers and Mathematics with Applications. His current research interests include interconnection networks, discrete mathematics, computation theory, graph theory, algorithm analysis, machine learning and data science.