

Lecture Notes in Electrical Engineering 572

Qilian Liang

Wei Wang

Jiasong Mu

Xin Liu

Zhenyu Na

Bingcai Chen *Editors*

# Artificial Intelligence in China

Proceedings of the International  
Conference on Artificial Intelligence in  
China

 Springer

# Lecture Notes in Electrical Engineering

## Volume 572

### Series Editors

Leopoldo Angrisani, Department of Electrical and Information Technologies Engineering, University of Napoli Federico II, Naples, Italy

Marco Arteaga, Departament de Control y Robótica, Universidad Nacional Autónoma de México, Coyoacán, Mexico

Bijaya Ketan Panigrahi, Electrical Engineering, Indian Institute of Technology Delhi, New Delhi, Delhi, India

Samarjit Chakraborty, Fakultät für Elektrotechnik und Informationstechnik, TU München, Munich, Germany

Jiming Chen, Zhejiang University, Hangzhou, Zhejiang, China

Shanben Chen, Materials Science and Engineering, Shanghai Jiao Tong University, Shanghai, China

Tan Kay Chen, Department of Electrical and Computer Engineering, National University of Singapore, Singapore, Singapore

Rüdiger Dillmann, Humanoids and Intelligent Systems Laboratory, Karlsruhe Institute for Technology, Karlsruhe, Germany

Haibin Duan, Beijing University of Aeronautics and Astronautics, Beijing, China

Gianluigi Ferrari, Università di Parma, Parma, Italy

Manuel Ferre, Centre for Automation and Robotics CAR (UPM-CSIC), Universidad Politécnica de Madrid, Madrid, Spain

Sandra Hirche, Department of Electrical Engineering and Information Science, Technische Universität München, Munich, Germany

Faryar Jabbari, Department of Mechanical and Aerospace Engineering, University of California, Irvine, CA, USA

Limin Jia, State Key Laboratory of Rail Traffic Control and Safety, Beijing Jiaotong University, Beijing, China

Janusz Kacprzyk, Systems Research Institute, Polish Academy of Sciences, Warsaw, Poland

Alaa Khamis, German University in Egypt El Tagamoa El Khames, New Cairo City, Egypt

Torsten Kroeger, Stanford University, Stanford, CA, USA

Qilian Liang, Department of Electrical Engineering, University of Texas at Arlington, Arlington, TX, USA

Ferran Martin, Departament d'Enginyeria Electrònica, Universitat Autònoma de Barcelona, Bellaterra, Barcelona, Spain

Tan Cher Ming, College of Engineering, Nanyang Technological University, Singapore, Singapore

Wolfgang Minker, Institute of Information Technology, University of Ulm, Ulm, Germany

Pradeep Misra, Department of Electrical Engineering, Wright State University, Dayton, OH, USA

Sebastian Möller, Quality and Usability Laboratory, TU Berlin, Berlin, Germany

Subhas Mukhopadhyay, School of Engineering & Advanced Technology, Massey University, Palmerston North, Manawatu-Wanganui, New Zealand

Cun-Zheng Ning, Electrical Engineering, Arizona State University, Tempe, AZ, USA

Toyoaki Nishida, Graduate School of Informatics, Kyoto University, Kyoto, Japan

Federica Pascucci, Dipartimento di Ingegneria, Università degli Studi "Roma Tre", Rome, Italy

Yong Qin, State Key Laboratory of Rail Traffic Control and Safety, Beijing Jiaotong University, Beijing, China

Gan Woon Seng, School of Electrical & Electronic Engineering, Nanyang Technological University, Singapore, Singapore

Joachim Speidel, Institute of Telecommunications, Universität Stuttgart, Stuttgart, Germany

Germano Veiga, Campus da FEUP, INESC Porto, Porto, Portugal

Haitao Wu, Academy of Opto-electronics, Chinese Academy of Sciences, Beijing, China

Junjie James Zhang, Charlotte, NC, USA

The book series *Lecture Notes in Electrical Engineering* (LNEE) publishes the latest developments in Electrical Engineering - quickly, informally and in high quality. While original research reported in proceedings and monographs has traditionally formed the core of LNEE, we also encourage authors to submit books devoted to supporting student education and professional training in the various fields and applications areas of electrical engineering. The series cover classical and emerging topics concerning:

- Communication Engineering, Information Theory and Networks
- Electronics Engineering and Microelectronics
- Signal, Image and Speech Processing
- Wireless and Mobile Communication
- Circuits and Systems
- Energy Systems, Power Electronics and Electrical Machines
- Electro-optical Engineering
- Instrumentation Engineering
- Avionics Engineering
- Control Systems
- Internet-of-Things and Cybersecurity
- Biomedical Devices, MEMS and NEMS

For general information about this book series, comments or suggestions, please contact [leontina.dicecco@springer.com](mailto:leontina.dicecco@springer.com).

To submit a proposal or request further information, please contact the Publishing Editor in your country:

#### **China**

Jasmine Dou, Associate Editor ([jasmine.dou@springer.com](mailto:jasmine.dou@springer.com))

#### **India, Japan, Rest of Asia**

Swati Meherishi, Executive Editor ([Swati.Meherishi@springer.com](mailto:Swati.Meherishi@springer.com))

#### **Southeast Asia, Australia, New Zealand**

Ramesh Nath Premnath, Editor ([ramesh.premnath@springernature.com](mailto:ramesh.premnath@springernature.com))

#### **USA, Canada:**

Michael Luby, Senior Editor ([michael.luby@springer.com](mailto:michael.luby@springer.com))

#### **All other Countries:**

Leontina Di Cecco, Senior Editor ([leontina.dicecco@springer.com](mailto:leontina.dicecco@springer.com))

**\*\* Indexing: The books of this series are submitted to ISI Proceedings, EI-Compendex, SCOPUS, MetaPress, Web of Science and Springerlink \*\***

More information about this series at <http://www.springer.com/series/7818>

Qilian Liang · Wei Wang ·  
Jiasong Mu · Xin Liu · Zhenyu Na ·  
Bingcai Chen  
Editors

# Artificial Intelligence in China

Proceedings of the International Conference  
on Artificial Intelligence in China

 Springer

*Editors*

Qilian Liang  
Department of Electrical Engineering  
University of Texas at Arlington  
Arlington, TX, USA

Jiasong Mu  
Department of Electronic  
and Communication Engineering  
Tianjin Normal University  
Tianjin, China

Zhenyu Na  
School of Information Science  
and Technology  
Dalian Maritime University  
Dalian, Liaoning, China

Wei Wang  
Tianjin, China

Xin Liu  
School of Information and Communication  
Engineering  
Dalian University of Technology  
Dalian, Liaoning, China

Bingcai Chen  
School of Computer Science  
and Technology  
Dalian University of Technology  
Dalian, Liaoning, China

ISSN 1876-1100

ISSN 1876-1119 (electronic)

Lecture Notes in Electrical Engineering

ISBN 978-981-15-0186-9

ISBN 978-981-15-0187-6 (eBook)

<https://doi.org/10.1007/978-981-15-0187-6>

© Springer Nature Singapore Pte Ltd. 2020

This work is subject to copyright. All rights are reserved by the Publisher, whether the whole or part of the material is concerned, specifically the rights of translation, reprinting, reuse of illustrations, recitation, broadcasting, reproduction on microfilms or in any other physical way, and transmission or information storage and retrieval, electronic adaptation, computer software, or by similar or dissimilar methodology now known or hereafter developed.

The use of general descriptive names, registered names, trademarks, service marks, etc. in this publication does not imply, even in the absence of a specific statement, that such names are exempt from the relevant protective laws and regulations and therefore free for general use.

The publisher, the authors and the editors are safe to assume that the advice and information in this book are believed to be true and accurate at the date of publication. Neither the publisher nor the authors or the editors give a warranty, expressed or implied, with respect to the material contained herein or for any errors or omissions that may have been made. The publisher remains neutral with regard to jurisdictional claims in published maps and institutional affiliations.

This Springer imprint is published by the registered company Springer Nature Singapore Pte Ltd. The registered company address is: 152 Beach Road, #21-01/04 Gateway East, Singapore 189721, Singapore

# Contents

<b>Global Descriptors of Convolution Neural Networks for Remote Scene Images Classification</b> . . . . .	1
Q. Wang, Qian Ning, X. Yang, Bingcai Chen, Yinjie Lei, C. Zhao, T. Tang, and R. Hu	
<b>Plant Diseases Identification Based on Binarized Neural Network</b> . . . . .	12
Xiufu Pu, Qian Ning, Yinjie Lei, Bingcai Chen, Tiantian Tang, and Ruiheng Hu	
<b>Hand Detection Based on Multi-scale Fully Convolutional Networks</b> . . . . .	20
Yibo Li, MingMing Shi, and Xiangbo Lin	
<b>Research on UAV Cluster’s Operation Strategy Based on Reinforcement Learning Approach</b> . . . . .	28
Yi Mao, and Yuxin Hu	
<b>Analysis and Experimental Research on Data Characteristics of BDS Positioning Error</b> . . . . .	36
He Li, Yi Mao, Yongjie Yan, and Xiaozhu Shi	
<b>Design of Elderly Fall Detection Based on XGBoost</b> . . . . .	46
Min Xiao, Yuanjian Huang, Yuanheng Wang, and Weidong Gao	
<b>Segmentation of Aerial Image with Multi-scale Feature and Attention Model</b> . . . . .	58
Shiyu Hu, Qian Ning, Bingcai Chen, Yinjie Lei, Xinzhi Zhou, Hua Yan, Chengping Zhao, Tiantian Tang, and Ruiheng Hu	
<b>Recurrent Neural Detection of Time–Frequency Overlapped Interference Signals</b> . . . . .	67
Qianqian Wu, Zhuo Sun, and Xue Zhou	

<b>Risk Analysis of Lateral Collision of Military and Civil Aviation Aircraft Based on Event Model</b> .....	76
Guhao Zhao, Shaojie Mao, Yi Mao, Xiaoqiang Zhang, and Yarong Wu	
<b>Imbalanced Data Classification with Deep Support Vector Machines</b> .....	87
Li Zhang, Wei Wang, Mengjun Zhang, and Zhixiong Wang	
<b>An Incident Identification Method Based on Improved RCNN</b> .....	96
Han He, Haijun Zhang, Sheng Lv, and Bingcai Chen	
<b>Latency Estimation of Big Data Processing Under the MapReduce Framework with Coupling Effects</b> .....	105
Di Lin, Lingshuang Cai, Xiaofeng Zhang, Xiao Zhang, and Jiazhi Huo	
<b>Zone-Based Resource Allocation Strategy for Heterogeneous Spark Clusters</b> .....	113
Yao Qin, Yu Tang, Xun Zhu, Chuanxiang Yan, Chenyao Wu, and Di Lin	
<b>Battle Prediction System in StarCraft Combined with Topographic Considerations</b> .....	122
ChengZhen Meng, Yu Tang, ChenYao Wu, and Di Lin	
<b>Task Scheduling Strategy for Heterogeneous Spark Clusters</b> .....	131
Yu Liang, Yu Tang, Xun Zhu, Xiaoyuan Guo, Chenyao Wu, and Di Lin	
<b>Research on Multi-priority Task Scheduling Algorithms for Mobile Edge Computing</b> .....	139
Yanrong Zhu, Yu Tang, Chenyao Wu, and Di Lin	
<b>Microblog Rumor Detection Based on Comment Sentiment and CNN-LSTM</b> .....	148
Sheng Lv, Haijun Zhang, Han He, and Bingcai Chen	
<b>A Guideline for Object Detection Using Convolutional Neural Networks</b> .....	157
Xingguo Zhang, Guoyue Chen, Kazuki Saruta, and Yuki Terata	
<b>Research on Prediction Model of Gas Emission Based on Lasso Penalty Regression Algorithm</b> .....	165
Qian Chen, and Lianbing Huang	
<b>Water Meter Reading Area Detection Based on Convolutional Neural Network</b> .....	173
Jianlan Wu, Yangan Zhang, and Xueguang Yuan	
<b>A Dependency-Extended Method of Multi-pattern Matching for RDF Graph</b> .....	180
Yunhao Sun, Fengyu Li, Guanyu Li, Heng Chen, and Wei Jiang	

**Machine Learning for RF Fingerprinting Extraction and Identification of Soft-Defined Radio Devices** . . . . . 189  
 Su Hu, Pei Wang, Yaping Peng, Di Lin, Yuan Gao, Jiang Cao, and Bin Yu

**Analysis on Suppression of Echo Signal of Target Body and Translation in Micro-Doppler Signal Processing** . . . . . 205  
 Tang Bo, and Sun Qiang

**Weighted Least Square Support Vector Regression Method with GGP-Based Sequential Sampling** . . . . . 212  
 Yang Guo, Jiang Cao, Qi Ouyang, and Shaochi Cheng

**Data Stream Adaptive Partitioning of Sliding Window Based on Gaussian Restricted Boltzmann Machine** . . . . . 220  
 Wei Wang, and Mengjun Zhang

**Intrusion Detection Based on Convolutional Neural Network in Complex Network Environment** . . . . . 229  
 Yunfeng Zhou, Xuezhong Zhu, Su Hu, Di Lin, and Yuan Gao

**Application of Neural Network in Performance Evaluation of Satellite Communication System: Review and Prospect** . . . . . 239  
 Shaochi Cheng, Yuan Gao, Jiang Cao, Yang Guo, Yanchang Du, and Su Hu

**Construction of Marine Target Detection Dataset for Intelligent Radar Application** . . . . . 245  
 Hao Ding, Ningbo Liu, Wei Zhou, Yonghua Xue, and Jian Guan

**Pedestrian Retrieval Using Valuable Absence Augmentation** . . . . . 254  
 Xiaolong Hao, Shuang Liu, Zhong Zhang, and Tariq S. Durrani

**An End-to-End Neural Network Model for Blood Pressure Estimation Using PPG Signal** . . . . . 262  
 Cuicui Wang, Fan Yang, Xueguang Yuan, Yangan Zhang, Kunliang Chang, and Zhengyang Li

**Concept Drift Detection Based on Kolmogorov–Smirnov Test** . . . . . 273  
 Zhixiong Wang, and Wei Wang

**Millimeter-Wave Beamforming of UAV Communications for Small Cell Coverage** . . . . . 281  
 Weizhi Zhong, Lei Wang, Qiuming Zhu, Xiaomin Chen, and Jianjiang Zhou

**The Feasibility Analysis of the Application of Ensemble Learning to Operational Assistant Decision-Making** . . . . . 289  
 Xiang Wei, and Xueman Fan

<b>A Review of Artificial Intelligence for Games</b> .....	298
Xueman Fan, J. Wu, and L. Tian	
<b>Intelligent Exhaust System of Cross-Linked Workshop</b> .....	304
Yan-ting Xu, and Yongjie Yang	
<b>Combined with DCT, SPIHT and ResNet to Identify Ancient Building Cracks from Aerial Remote Sensing Images</b> .....	313
Tiantian Tang, Bingcai Chen, and Ruiheng Hu	
<b>Design and Construction of Intelligent Voice Control System</b> .....	319
Dapeng Zhu, Shu Liu, and Chao Liu	
<b>Estimation of Sea Clutter Distribution Parameters Using Deep Neural Network</b> .....	326
Guoqing Wang, Hao Ding, Chaopu Wang, and Ningbo Liu	
<b>Maritime Target Trajectory Prediction Model Based on the RNN Network</b> .....	334
Jialong Jin, Wei Zhou, and Baichen Jiang	
<b>Industrial Ventilator Monitoring System Based on Android</b> .....	343
Junjiao Zhang, Yongjie Yang, and Zhongxing Huo	
<b>An Overview of Blockchain-Based Swarm Robotics System</b> .....	353
Yanchang Du, Jiang Cao, Junsong Yin, and Shuang Song	
<b>A Transmission Method for Intra-flight Ad Hoc Networks Based on Business Classification</b> .....	361
Songhua Huang	
<b>3D Statistical Resolution Limit of Two Close Spaced Targets for Active Array in the GLRT Context</b> .....	369
Pei Peng, Yunlei Zhang, and Jianbin Lu	
<b>A Scene Semantic Recognition Method of Remote Sensing Images Based on CSIFT and PLSA</b> .....	378
Yan-li Sun, Wei Zhou, Ya-zhou Zhang, and Jialong Jin	
<b>Applications of Brain-Inspired Intelligence in Intelligentization of Command and Control System</b> .....	385
Shuangling Wang, Chao Liu, Songhua Huang, and Kan Yi	
<b>The Integrative Technology of Testability Design and Fault Diagnosis for Complex Electronic Information System</b> .....	391
Leqing Ou, and Fang Bai	
<b>Chinese Named Entity Recognition with Changed BiLSTM and CRF</b> .....	398
Jie Ren, Jing Liang, and Chenkai Zhao	

**Key Problems and Solutions of the Application of Artificial Intelligence Technology** ..... 407  
 Guangxia Zhou

**Recent Advances for Smart Air Traffic Management: An Overview** ..... 415  
 Chao Jiang

**Application of GRIB Data for 4D Trajectory Prediction** ..... 422  
 Yibing Yin, and Ming Tong

**Weibo Rumor Detection Method Based on User and Content Relationship** ..... 431  
 Zhongyue Zhou, Haijun Zhang, and Weimin Pan

**Improved HyperD Routing Query Algorithm Under Different Strategies** ..... 435  
 Xiaoyu Tao, Bo Ning, Haowen Wan, and Jianfei Long

**Computer-Aided Diagnosis of Mild Cognitive Impairment Based on SVM** ..... 442  
 Sichong Chen, Wenjing Jiang, Bingjia Liu, and Zhiqiong Wang

**Details for Person Re-identification Baseline** ..... 452  
 Zhong Zhang, Haijia Zhang, and Shuang Liu

**An Ontology for Decision-Making Support in Air Traffic Management** ..... 458  
 Yin Sheng, Xi Chen, Haijian Mo, Xin Chen, and Yang Zhang

**Flight Conflict Detection and Resolution Based on Digital Grid** ..... 467  
 Yang Yi, Ming Tong, and LiuXi

**Abnormality Diagnosis of Musculoskeletal Radiographs Combined with Shallow Texture Features** ..... 480  
 Yunxue Shao, and Xin Wang

**An ATM Knowledge Graph-Based Method of Dynamic Information Fusion and Correlation Analysis** ..... 487  
 Qiucheng Xu, Yongjie Yan, Yungang Tian, Weiyu Jiang, and Jinglei Huang

**Research of Lung Cancer-Assisted Diagnosis Algorithm Based on Multi-scale Convolution Kernel Network** ..... 497  
 Yunfei Li, Chuangang Li, Yijia Cao, Yue Zhao, and Zhiqiong Wang

**Design for Interference Suppression Intelligent Controller Based on Minimax Theory** ..... 506  
 Ling Chang, Chaoying Shan, and Huifang Wei

<b>Research on System Architecture Based on Deep Learning Convolutional Neural Network</b> .....	514
Caijuan Chen, and Ying Tong	
<b>Research on the Development and Application of Unmanned Aerial Vehicles</b> .....	523
Kai Qiu, Chifei Zhou, Yijing Liu, Lanlan Gao, Xianzhou Dong, and Jiang Cao	
<b>Recent Development of Commercial Satellite Communications Systems</b> .....	531
Jinhui Huang, and Jiang Cao	
<b>Feature-Aware Adaptive Denoiser-Selection for Compressed Image Reconstruction</b> .....	537
Mengke Ma, Dongqing Li, Shaohua Wu, and Qinyu Zhang	
<b>AI-Assisted Complex Wireless Network Evaluation Using Dynamic Ranking Scheme</b> .....	546
Yuan Gao, Jiang Cao, Weigui Zhou, Chao Qing, Hong Ao, Su Hu, Junsong Yin, ShuangShuang Wang, Xiangyang Li, and Haosen Yu	
<b>Re-sculpturing Semantic Web of Things as a Strategy for Internet of Things' Intrinsic Contradiction</b> .....	554
Jingmin An, Guanyu Li, Bo Ning, Wei Jiang, and Yunhao Sun	
<b>The Precise Location Method for Initial Target Based on Fused Information</b> .....	563
Yan Junhua, Xu Zhenyu, Zhang Yin, Yang Yong, and Su Kai	
<b>CMnet: A Compact Model for License Plate Detection</b> .....	576
Yao Cheng, Xin Zhou, and Bo Ning	
<b>Parallelization of Preprocessing for Automatic Detection of Pulmonary Nodules in 3D CT Images</b> .....	584
Junpeng Weng, Yu Tang, and Di Lin	
<b>Predicting the Trajectory Tracking Control of Unmanned Surface Vehicle Based on Deep Learning</b> .....	591
Wenli Sun, and Xu Gao	
<b>Coordinated Learning for Lane Changing Based on Coordination Graph and Reinforcement Learning</b> .....	599
Hao Zuo, Huaiwei Si, Nan Ding, Xin Wang, and Guozhen Tan	
<b>Pretreatment Method of Deep Learning Method for Target Detection in Sea Clutter</b> .....	608
Yanan Xu, Ningbo Liu, Hao Ding, Yonghua Xue, and Jian Guan	

**A Novel Endmember Extraction Method Based on Manifold Dimensionality Reduction** . . . . . 615  
Xiaoyan Tang, and Shangzheng Liu

**Research on Chinese Short Text Clustering Ensemble via Convolutional Neural Networks** . . . . . 622  
Haowen Wan, Bo Ning, Xiaoyu Tao, and Jianfei Long

**A Survey of Moving Objects kNN Query in Road Network Environment** . . . . . 629  
Wei Jiang, Guanyu Li, Jingmin An, Yunhao Sun, Heng Chen, and Xinying Chen

**The Importance of Researching and Developing the Semantic Web of Things** . . . . . 637  
Xinying Chen, Guanyu Li, Yunhao Sun, Heng Chen, and Wei Jiang

**Facial Expression Recognition Based on Strengthened Deep Belief Network with Eye Movements Information** . . . . . 645  
Bo Lu, and Xiaodong Duan

**Real Image Reproduction Algorithm Based on Sigmoid-iCAM Color Model** . . . . . 653  
Dongyue Xiao, and Xiaoyan Tang

**Game Traffic Classification Based on DNS Domain Name Resolution** . . . . . 659  
Xingchen Xu, Mei Nian, and Bingcai Chen



# Global Descriptors of Convolution Neural Networks for Remote Scene Images Classification

Q. Wang<sup>1</sup>, Qian Ning<sup>1,2(✉)</sup>, X. Yang<sup>1</sup>, Bingcai Chen<sup>3,4</sup>, Yinjie Lei<sup>1</sup>, C. Zhao<sup>1</sup>,  
T. Tang<sup>1,2,3,4</sup>, and R. Hu<sup>1,2,3,4</sup>

<sup>1</sup> College of Electrical & Information Engineering,  
Sichuan University, Chengdu 610065, China  
ningq@scu.edu.cn

<sup>2</sup> School of Physics & Electronics,  
Xinjiang Normal University, Urumqi 830054, China

<sup>3</sup> School of Computer Science & Technology at Dalian University  
of Technology, Dalian 116024, China

<sup>4</sup> School of Computer Science & Technology at Xinjiang Normal University,  
Urumqi 830054, China

**Abstract.** Nowadays, the deep learning-based methods have been widely used in the scene-level-based image classification. However, the features automatically obtained from the last fully connected (FC) layer of single CNN without any process have little effect because of high dimensionality. In this paper, we propose a simple enhancing scene-level feature description method for remote sensing scene classification. Firstly, the principal component analysis (PCA) transformation is adopted in our research for reducing redundant dimensionality. Secondly, a new method is used to fuse features obtained by PCA transformation. Finally, the random forest classifier applying to classification makes a significant effect on compressing the training procedure. The results of experiments on the public dataset describe that feature fusion with PCA transformation performs great classification effect. Moreover, compared with the classifier softmax, the random forest classifier outperforms the softmax classifier in the training procedure.

**Keywords:** Remote sensing image (RSI) · Global feature descriptors · Feature fusion · Scene classification

## 1 Introduction

More recently, in the field of RSI investigation, RSI scene classification [1] is one of the most important processes. For RSI classification, image semantic understanding is generally reflected by feature descriptors. Therefore, the key to classifying is features. In our research, we focus on the investigation of RSI feature

descriptors, premeditating the feature extraction as a critical step to obtain a great classification performance. Existing RSI features extraction research methods are primarily divided into local features extracting methods and global features extracting methods. For the former, there exist two types of methods, corner feature extraction methods and edge feature extraction methods. In the past, corner feature descriptor was the main job in feature extraction, such as features from accelerated segment test (FAST) [2], oriented fast and rotated brief (ORB) [2]. However, the curves of edge are discontinuous. Hence, they have limitations on the description of scene semantic information.

Numerous algorithms have been introduced for edge feature descriptor extraction. Signature of Histograms of Orientations (SHOT) [3] and Raster Operations Units (ROPS) [4] are based on the histogram statistics for local descriptors extraction, but they are low expression for semantic information in most of the experiments. In summarize, local descriptors extracting methods are considerably depending on the experiences of researchers, and higher requirements for extracted feature descriptors are necessary for these methods.

Among all kinds of methods to extract features, comprehensive feature descriptors can be obtained by deep learning-based methods, which help to enhance the ability of image description greatly. In 2012, Krizhevsky et al. [5] proposed a sensational deep learning neural network for image classification, which picks up the 2012 image recognition contest champion. From then on, the CNN architecture detonated the application boom of neural networks. Simultaneously, more deep CNN architectures were proposed after AlexNet [5], such as VGGNet [6], ResNet [7]. Due to the convenience of extracting features and the better result of classification, they are applied widely in many aspects of image recognition. Liu et al. [8] proposed to concatenate features extracted from convolutional layers of CaffeNet and VGG-VD16 to deep descriptors.

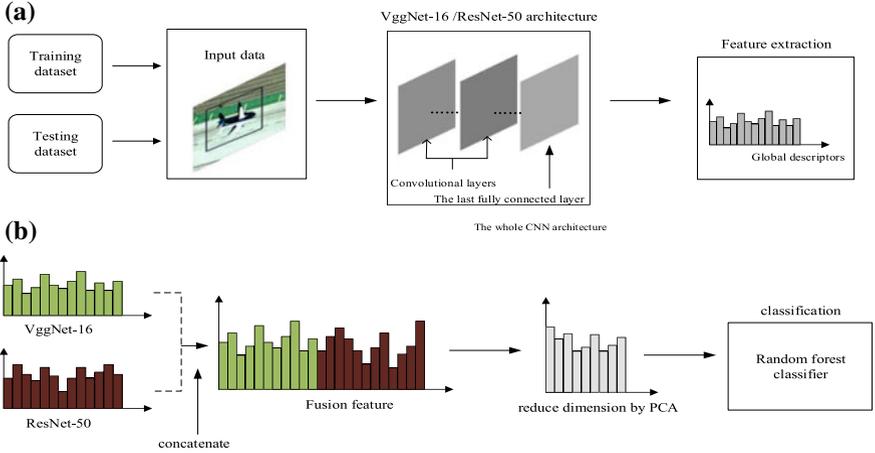
In this paper, we propose a method to accelerate the speed of RSI classification model training with significant performance increase. Specifically, we first obtain features from the last FC layer of two deep CNN models. Then we reduce the feature vector dimension utilizing PCA transformation. For accelerating the training speed and exploring a better effect on classification result, we propose an optimize and simple way to generate feature vector by concatenating the features from two types of different CNN models.

## 2 Proposed Method

The details of the proposed method are shown in Fig. 1. The main content consists of the following three parts: global descriptors extracting, feature fusion, and reducing dimensions. The procedure is organized as follows. The first part extracts global feature descriptors from the last fully connected layers, including a sample of the training set and the used pre-train CNN. Two types of pre-train CNN, VGGNet-16 and ResNet-50, are introduced to extract global feature descriptors. The second part is the details of the proposed method.

For the first step (Fig. 1a), the training set and testing set are used as the input of a CNN mode to extract the global feature descriptors from the last fully connected layer.

For the third step (Fig. 1b), the features of every input data obtained from the first part are concatenated to form the complete global feature descriptors. With a PCA transformation to reduce the dimension, the last classification results are given by the random forest classifier.



**Fig. 1.** Framework of proposed method. **a** Is the process of feature extraction. **b** Proposed method: concatenating features followed by PCA transformation.

## 2.1 Global Descriptors Extracting

In recent years, many CNN architectures have been proposed. Most of them perform a great effect on a large testing set. Such as VGGNet performs better on classification than AlexNet or CaffeNet. ResNet can obtain significant accuracy with deeper architecture and fewer parameters. At the first step, RSIs enter into VGGNet-16 and ResNet-50, respectively, for feature extracting, and the result is the global descriptor, which refers to the relationship between the extracted features and the entire image.

**Feature extraction:** A pre-train CNN mode serves as the feature extractor in many researches. As using the CNN as feature extractor, the minimal image shift has no effect on the last feature vectors because of the properties of convolution and pooling calculation. Hence, the obtained features have powerful fit abilities and make no influence on the classification result. In addition, because of this stability, it fits to every kind of image for feature extraction. When we apply a CNN for feature extraction, a popular feature extraction strategy is extracting an activation vector from the last fully connected layer (including the classifier layer) [9].

## 2.2 Feature Fusion and the Dimension Reduction

Existing deep learning pre-trained CNN models are used as the feature extractor to extract the feature from the final FC layers (include the last classification layer). Although the feature can be utilized to train the classifier directly, effective features extracted by only a single CNN pre-trained model are not enough, which will lead to a disappointing effect. Hence, an efficacious way to solve this question, feature fusion, is proposed.

**Feature fusion:** Deep feature fusion is a new solution to handle complex data. In 2014, two MIT engineers developed deep feature synthesis [10]. Most prediction decisions rely on the features descriptors based on input images in the vision classification tasks. Hence, it is necessary to overcome the obstacles of data dependence. Feature fusion refers to concatenating global features descriptors extracted from several different pre-trained CNN models. Vectors obtained by these models expand the dimension of the final vector by vector-spliced which is an efficient method to mitigate data dependence. In addition, the key advantage of feature fusion is new features obtained in this process, which can improve the performance of classification.

**Reduce dimension:** Dimensionality reduction, as the name implies, means feature selection and feature extraction. Since principal component analysis [11] was successfully proposed, applying PCA transformation to reduce dimension becomes a mainstream tendency. In the proposed method, PCA, as an important processing technology, is introduced for feature descriptors distinguishing and dimension reducing. With PCA more consummate, the field of data it can handle becomes wider. It is also the main technology for compressing the time of training process without losing the quality of a model. The main process for PCA is to transform the original data onto a set of linearly independent representations of each dimension through linear transformation, which reduces the dimension of input data set while maintaining the feature of the largest contribution of the data set in the data set. The final result is the key feature components of all the features.

## 3 Experiments and Analyses

### 3.1 UC Merced Land Use Dataset Description

In this section, we investigate the performance of the proposed methods on the “UC Merced Land Use” dataset<sup>1</sup> [12] extracted from large images from the US Geological Survey National Map Urban Area Imagery collection for various urban areas around the country. This dataset contains 21 classes. Each class includes 100 images with the size of  $256 \times 256$  pixels in the color space of red–green–blue with different space structure, color distribute, region cover, and object cover. Every image is operated by rotating.

---

<sup>1</sup> <http://vision.Ucmerced.edu/datasets/landuse.html>.

### 3.2 Experimental Introduction

For input data, 75% images in each class serve as the training set and the remaining serve as the testing set. In experiments, the global feature descriptors are extracted from two pre-trained CNN models consisting of VGGNet-16 and ResNet-50, which are trained on the ImageNet dataset. The dimensions of global feature descriptors are  $1 \times 1000$ . The random forest is applied for training and classification. The confusion matrices performed the result of our proposed method; the training time is analyzed on the different methods to train.

### 3.3 Discuss Different CNN Models with PCA

The comparison between two types of CNN-based features classification is shown in Tables 1 and 2. The result of the classification on VGGNet-16-based and ResNet-50-based features without PCA transformation is displayed in Table 1 and the classification details of two types of CNN-based features with PCA transformation are performed in Table 2. The ratio of PCA transformation is set as 95%. The comparison in tables demonstrates that VGGNet-16 performs better classification effect. VGGNet-16-based features are better discrimination, especially in some similar categories, such as “beach,” “parking lot,” and “runway”, which is because the initial parameters in VGGNet-16 are much richer.

From two tables, we can see that using PCA transformation performs greatly for both types pre-trained CNN models, especially for the ResNet-50, which has improved about 8%. In general, PCA transformation help to improve the description ability of the global features.

### 3.4 Analysis of the Proposed Method

In this section, we research the confusion matrix on the 21-classes public remote dataset. Figure 2 describes the confusion matrix of proposed method, which includes feature fusion and PCA transformation. The confusion matrix is analyzed via using 25% of the training dataset. As confusion matrix is shown, the entry in the  $i$ th row and  $j$ th column means the rate of RSI belongs to the  $i$ th class and classifies to  $j$ th class. The classification results are proposed as percentages.

In Fig. 2, the average accuracies of classification for proposed method are 86.78%. It performs great ability (the accuracy of classification  $\geq 90\%$ ) on the classes, such as “airplane,” “agricultural,” “baseballdiamond,” “chaparral,” “forest,” “golf course,” “harbor,” “overpass,” “tennis court,” “river.” The features extracted from these RSI include considerable information, which helps classify correctly.

Moreover, some classes obtain poor classification effect, such as “dense residential,” “medium residential.” This is the reason that high dimensional features of these classes are too similar to distinguish. In addition, several classes include plenty of building elements, which results an error decision.

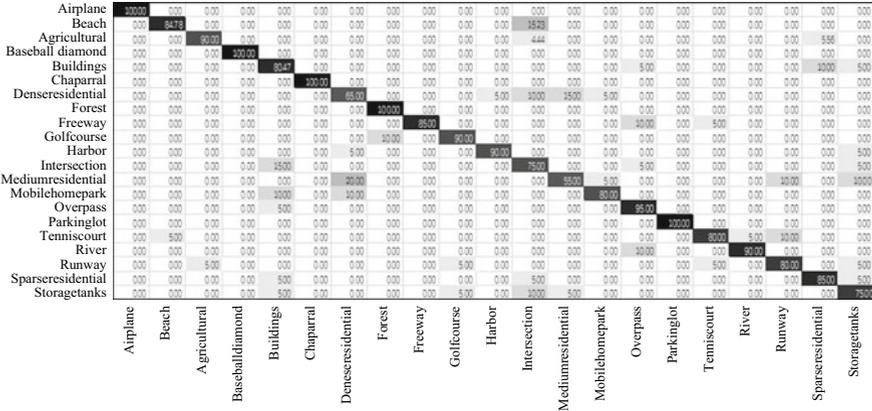
Table 3 presents the comparison between state-of-art methods and our proposed method. These existing methods are detailed in [8, 12–14]. As we can see

**Table 1.** Classification accuracies without PCA transformation. OA: overall average

Class	Airplane	Beach	Agricultural	Baseball-diamond	Buildings	Chaparral	Dense-residential	Forest	Freeway	Golfcourse	Harbor
ResNet-50	0.875	0.313	0.5	0.688	0.375	0.938	0.125	0.875	0.688	1.0	0.563
VggNet-16	1.0	0.688	0.75	0.438	0.625	1.0	0.5	1.0	0.813	0.875	0.813
Class	Intersection	Medium-residential	Mobile-homepark	Overpass	Parkinglot	River	Runway	Sparse-residential	Storage-tanks	Tennis-court	OA
ResNet-50	0.313	0.25	0.625	0.625	0.313	0.938	0.313	0.25	0.5	0.813	0.554
VggNet-16	0.5	0.563	0.5	0.688	0.635	0.75	0.375	0.625	0.625	0.813	0.693

**Table 2.** Classification accuracies with PCA transformation. OA:overall average

Class	Airplane	Beach	Agricultural	Baseball-diamond	Buildings	Chaparral	Dense-residential	Forest	Freeway	Golfcourse	Harbor
ResNet-50	1.0	0.438	0.438	0.25	0.563	0.875	0.188	1.0	0.625	0.875	0.875
VggNet-16	1.0	0.688	0.688	0.75	0.625	1.0	0.5	1.0	0.875	0.938	0.75
Class	Intersection	Medium-residential	Mobile-homepark	Overpass	Parkinglot	River	Runway	Sparse-residential	Storage-tanks	Tennis-court	OA
ResNet-50	0.438	0.75	0.688	0.688	0.325	0.688	0.625	0.313	0.563	0.875	0.639
VggNet-16	0.438	0.688	0.688	0.5	0.75	0.75	0.188	0.563	0.688	0.813	0.715



**Fig. 2.** Confusion matrix for 21-category performed result of the proposed method (86.78%)

that our proposed method enhances the classification effect 1.69% over the best-existed results in [8, 12–14]. To sum up, our approach achieves a more favorable effect on this dataset because of the combination of feature fusion and PCA transformation.

**Table 3.** Overall classification accuracies on dataset

	Approaches	Overall accuracies (%)
State-of-art	BOVW [12]	76.81
	Texture [12]	76.91
	spck++ [14]	77.38
	Approach of [13]	75.33
	Strategy 1 of [8]	85.09
	<b>Our method</b>	<b>86.78</b>

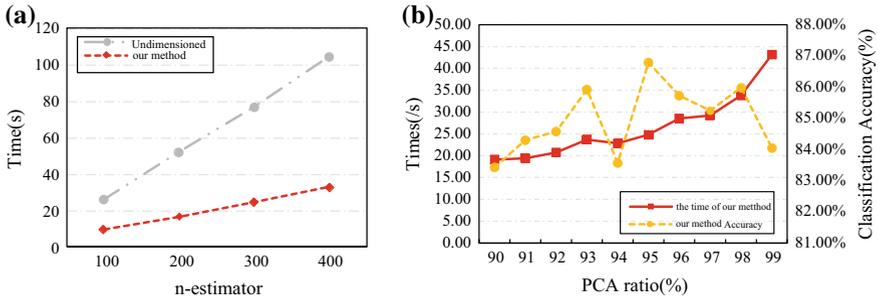
## 4 Discussion of Time

In this part, the time spent on the training process with different classifiers is compared. As Table 4 shown, applying Caffe framework to train the CNN architectures, VGGNet-16 and ResNet-50, based on GPU for acceleration need 4376 and 2437 s, individually. However, our proposed method with random forest for classifying based on the 21-category dataset just needs 24.81 seconds, which shortens over one hundred times. In addition, the classification accuracies of our method are 86.78%, which is higher than VGGNet-16 and ResNet-50. Moreover, after analyzing, PCA transformation helps to reduce the time for training, too.

**Table 4.** Time for training a model on dataset

Classifier	Pretain model	Accuracy (%)	Training time (s)
Softmax	VGGNet-16	78.3	4376
	ResNet-50	82.4	2437s
Random forest (with PCA)	VGGNet-16	70.8	15.73
	ResNet-50	63.7	10.45
	Our method	86.78	24.81
Random forest (no PCA)	VGGNet-16	72.3	54.07
	ResNet-50	56.9	55.45
	Fusion-feature	85.24	52.00

In Fig. 3a, two curves display two situations about the proposed method with several numbers of trees in a random forest. With the number increasing, the spending time increases, too. The gray line demonstrates the features without PCA transformation, training spending is slower than the other situation. In addition, as Fig. 3b shown, while the dimension (For proposed method, corresponding to the PCA ratio 90–99%, the dimension number of PCA transformation is separately 104, 116, 130, 147, 168, 194, 227, 274, 346, 487) number of PCA transformation increasing, the training process gets longer, too. On the other hand, when the PCA transformation ratio obtains 95% (The dimension numbers is 194), the classification accuracy attains the highest, which is 86.78%. Overall, whatever for time spending or classification performance, our proposed method performs a better effect on the total datasets.



**Fig. 3.** **a** Shows time changing with different n\_estimators; **b** shows the Pca transformation ratios influence the changing of training time and classification accuracy

## 5 Conclusion

In this paper, we investigate the global feature descriptors extracted from the last FC layer of CNN pre-trained models. Comparing to a single-model feature, the fusion features are more representative. Both pre-trained CNN-based features, VGGNet-16 and Resnet-50, are proposed to form the last global feature descriptors. The proposed method focuses on the most contribution features in both different CNN models. The result of experiment illustrates that feature fusion with a suitable dimension number of PCA transformation can enhance the performance of classification. Comprehensive evaluations of the public RSI scene classification perform the model training efficiency.

## References

1. Bian X et al (2017) Fusing local and global features for high-resolution scene classification. *IEEE J Sel Top Appl Earth Obs Remote Sens* 10(6):2889–2901
2. Rublee E et al (2011) ORB: an efficient alternative to SIFT or SURF. In: 2011 IEEE international conference on computer vision (ICCV). IEEE
3. Salti S, Tombari F, Di Stefano L (2014) SHOT: unique signatures of histograms for surface and texture description. *Comput Vis Image Underst* 125:251–264
4. Tombari, F, Salti S, Di Stefano L (2010) Unique signatures of histograms for local surface description. In: European conference on computer vision. Springer, Berlin, pp 356–369
5. Krizhevsky A, Sutskever I, Hinton GE (2012) Imagenet classification with deep convolutional neural networks. In: Advances in neural information processing systems, pp 1097–1105
6. Simonyan K, Zisserman A (2014) Very deep convolutional networks for large-scale image recognition. arXiv preprint [arXiv:1409.1556](https://arxiv.org/abs/1409.1556)
7. He K, Zhang X, Ren S, Sun J (2016) Deep residual learning for image recognition. In: Proceedings of the IEEE conference on computer vision and pattern recognition, pp 770–778
8. Liu N et al (2018) Exploiting convolutional neural networks with deeply local description for remote sensing image classification. *IEEE Access* 6:11215–11228
9. Nogueira K, Penatti OAB, dos Santos JA (2017) Towards better exploiting convolutional neural networks for remote sensing scene classification. *Pattern Recogn.* 61:539–556
10. Kanter JM, Veeramachaneni K (2015) Deep feature synthesis: Towards automating data science endeavors. In: 2015 IEEE international conference on data science and advanced analytics (DSAA), 36678. IEEE, pp 1–10
11. Ke, Y, Sukthankar R (2004) PCA-SIFT: a more distinctive representation for local image descriptors. In: Proceedings of the 2004 IEEE computer society conference on computer vision and pattern recognition, 2004, vol 2. IEEE
12. Yang Y, Newsam S (2010) Bag-of-visual-words and spatial extensions for land-use classification. In: Proceedings of the 18th SIGSPATIAL international conference on advances in geographic information systems. ACM, pp 270–279

13. Liu Q, Hang R, Song H, Li Z (2018) Learning multiscale deep features for high-resolution satellite image scene classification. *IEEE Trans Geosci Remote Sens* 56(1):117–126
14. Yang Y, Newsam S (2011) Spatial pyramid co-occurrence for image classification. In: 2011 IEEE international conference on computer vision (ICCV). IEEE, pp 1465–1472



# Plant Diseases Identification Based on Binarized Neural Network

Xiufu Pu<sup>1</sup>, Qian Ning<sup>1,2(✉)</sup>, Yinjie Lei<sup>1</sup>, Bingcai Chen<sup>3,4</sup>,  
Tiantian Tang<sup>2</sup>, and Ruiheng Hu<sup>2</sup>

<sup>1</sup> College of Electronics and Information Engineering, Sichuan University,  
Chengdu 610065, China

ningq@scu.edu.cn

<sup>2</sup> College of Physics and Electronics Engineering, Xinjiang Normal University,  
Urumqi 830054, China

<sup>3</sup> College of Computer Science and Technology Engineering,  
Dalian University of Technology, Dalian 116024, China

<sup>4</sup> College of Computer Science and Technology Engineering,  
Xinjiang Normal University, Urumqi 830054, China

**Abstract.** Although the use of the convolutional neural network (CNN) improved the accuracy of object recognition, it still had a long-running time. In order to solve these problems, the training and testing datasets were split at four different proportions to reduce the impact of inherent error. Using model fine-tuning, the model converged in a small number of iterations, and the average recognition accuracy of BWN test can reach 96.8%. In the segmented dataset, the recognition accuracy of the former was 4.7 percentage points higher than the latter by comparing color dataset and grayscale dataset, which proved that a certain amount of color features will have a positive impact on the model. The segmented dataset was 0.9 percentage points higher than the color dataset; it shows that the model focused more on features of contour and texture by eliminating the background of images. The experiments showed that the binarized convolutional neural network can effectively improve recognition efficiency and accuracy compared with traditional methods.

**Keywords:** Agricultural diseases · Binarized model · Image classification

## 1 Introduction

Plant diseases are one of the three natural disasters in China. In China, more than 250 billion kg of grain, fruits, vegetables, oil, and cotton is lost every year.

Visual inspection is one of the main traditional methods for diagnosing plant diseases. However, there are two problems: The judgments made by farmers based on experience are not all correct and the situation of plants will be worse without timely and effective treatment for diseases [1]. In order to realize the diagnosis of agricultural diseases rapidly and accurately, researchers have explored methods for identifying multiple plant diseases [2], using machine learning and image processing technology. Convolutional neural network is good at extracting the features of contour and texture

of leaves. Generally speaking, the deeper the network, the more the parameters and the larger models. It spends a long time to classify objects. In order to solve these problems, this paper proposes an effective way to classify plant diseases by using binarized convolutional neural networks. It aims to speed up the operation by binarizing the parameters.

## 2 Related Work

Kan et al. [3] extracted the contours and texture features of the leaves by radial basis function (RBF) neural network. The average recognition rate is 83.3%. Tan et al. [4] can effectively identify lesion area of soybean by calculating the color value of leaves and creating a multilayered BP neural network. The average recognition accuracy can reach 92.1%. Zhang et al. [5] used the cloning algorithm and K-nearest neighbor algorithm to classify leaves, which achieved a recognition rate of 91.37%. Wang et al. [6] used the support vector machine (SVM) to identify the leaves; the accuracy of the classifier can reach 91.41%.

Dyrmann et al. [7] used convolutional neural networks to classify plant images taken with mobile phones, and the average recognition accuracy reached 86.2%. Mohanty et al. [8] carried out experiments on 26 diseases of 14 kinds of plant; they choose two models, three datasets, and five datasets with different proportions, which also achieved good results. Lee et al. [9] explored how the CNN extracts features of leaves. They tested different methods and contrasted various experimental results. The results show that the CNN has a better effect on classification.

## 3 Dataset

This paper obtained 54,306 leaf images from PlantVillage by color, grayscale, and segmentation, which contains a total of 38 plant types. According to the number of different types of leaves in the dataset, the number of different kinds of leaf images ranges from 64 to 1166. In order to make up for the shortcomings, this paper expands the dataset by enhancing the exposure of the blade, changing the color of the image, and rotating the image. Rotating the image is to eliminate the effects of inherent bias [10]. Then, the images are labeled by category, and center cropped to a size of  $224 \times 224$ .

## 4 Convolutional Neural Networks

Generally speaking, to classify two objects there are two steps: data forward transmission and weight updating. When starting to train a model, there are two choices: one is to completely reset the parameters and train from scratch; the other is model fine-tuning. And the latter was used in this paper. Generally, the basic structure of CNN includes a feature extraction layer and a feature mapping layer. The former includes a convolution layer and a pooling layer, where each neuron is connected to the

acceptance domain of the previous layer, and then extracts features of that acceptance domain [11]. The process of forward transmission is shown in Formula 1.

$$f_{\text{out}} = f(w \dots (wf(wx + b) + b) \dots + b) \quad (1)$$

The back-propagation process is actually a process of weight update. In this paper, SGD and Adam are used to update the weight. The process of feature extraction and weight update is continuous, until the global optimal solution is found. In most experiments, the results are local optimum; it is necessary to adjust the learning rate and select the loss function, so that the network can find the global optimum solution.

The parameter update is shown in Formula (2).

$$W_{ij}^l = W_{ij}^l - \alpha \frac{\partial}{\partial W_{ij}^{(l)}} J(W, b) \quad (2)$$

## 5 Binarized Convolutional Neural Network

In the article [12], the parameters with single-precision floating point are converted into parameters that only occupy 1 bit, which theoretically reduces the memory space by 32 times. Moreover, the speed of the model is accelerated to about twice as fast. Symbolic functions can be expressed as:

$$\text{sign}(x) = \begin{cases} 1 & \text{if } x > 0 \\ -1 & \text{if } x \leq 0 \end{cases} \quad (3)$$

The binarized convolution neural network converts the weights and the activation values of hidden layers into 1 or  $-1$ . There are two ways of conversion: deterministic method and stochastic method. The former is simple and intuitive. If the weight or activation value is greater than 0, it is converted to 1; if it is less than 0, it is converted to  $-1$ . The latter calculates a probability  $p$  for the input. When  $p$  is greater than a threshold, it is  $+1$ , otherwise it is  $-1$ . Since the random numbers generated by hardware, which is more difficult to implement. Therefore, the first method is adopted in this paper.

In this paper, we take a method of approximating the real weights by using a binarized weight  $B$  and a scale factor  $\alpha$ . The process of conversion is shown in Formula (4), where  $\oplus$  represents the convolution operation of input and binarization weights.

$$I * W \approx (I \oplus B)\alpha \quad (4)$$

The binarized VGG16 network is used for experiments in this paper. Same as ordinary convolutional neural networks, the binarized network also includes the input layer, the hidden layer, and the output layer. The hidden layer includes convolution layer and pooling layer, where binarized convolution and pooling operation are used.

The forward transmission process of the binary network can be divided into four steps: first let the input pass through a Batch Normal, then binarize the input value, and binary convolution and pooling are used. Finally output the classification through a classifier. The weight is updated with full precision during the training process.

The forward transmission of binarized network:

$$x^k = \sigma(\text{BN}(W_b^k \cdot x^{k-1})) = \text{sign}(\text{BN}(W_b^k \cdot x^{k-1})) \quad (5)$$

The process of binarized model update is shown in Fig. 1.

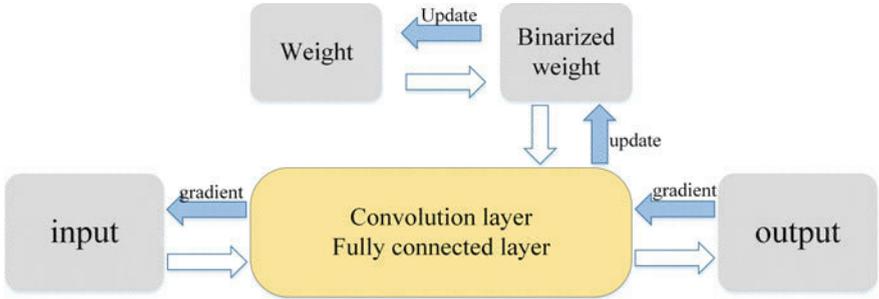


Fig. 1. Schematic diagram of binarized model training

## 6 Training and Discussion

### 6.1 Experiment Platform

The experimental environment is Ubuntu 16.04 LTS 64-bit system, using PyTorch as the deep learning open-source framework and using python as the programming language. The computer memory is 64G, equipped with Intel Xeon(R) CPU E5-1640 v4 3.6 GHz x12 processor. The graphics card is a NVIDIA GTX1080Ti.

### 6.2 Parameter Selection in Experiment

The train and test dataset are divided into multiple batches in this paper; each batch has 32 images. The full-precision model uses SGD to optimize the model with a learning rate of 0.005 and regularization coefficient of  $5e-4$ . The learning rate become 0.1 times of the original per 20 epoch. The binarized model uses Adam to optimize the model with learning rate of 0.001, regularization coefficient of  $1e-5$ . The learning rate become 0.1 times of the original per 30 epoch.

In order to prevent over-fitting, four different proportions are set: train set: 80, 60, 30, 20%; test set: 20, 30, 60, 80%. The more the sample ratio, the smaller the influence of experimental inherent on the results. At the same time, in order to make a fair comparison, the hyper-parameters are standardized.

In order to compare the effect of the dataset under different conditions, the collected images are divided into color dataset, gray dataset, and segmented dataset. The segmented dataset eliminates the influence of the background on the picture.

### 6.3 Analysis and Discussion

The results are shown in the line chart. It can be seen from the chart, under the same condition, the average accuracy of the full-precision model is slightly higher than that of the binarized model. Due to the high initial learning rate, the accuracy of the two networks is improved rapidly before 20 epochs, and eventually, it tends to be stable.

It can be seen from the green polyline, because of the fine-tuning of the model the initial accuracy of the full-precision model is higher. The color, segmentation, and grayscale datasets, respectively, reach the accuracy of 0.6, 0.7, and 0.5. For the red polyline, even if the parameter of trained model is used, the binarized parameter leads to lower initial accuracy, but the accuracy tends to be stable after 30 epochs. Four proportion datasets are set in this paper. It can be seen from the last line chart that the green polyline and red polyline have a higher accuracy, followed by yellow and blue polyline. It proves that the more the training sample, the more features can be extracted to train networks (Fig. 2).

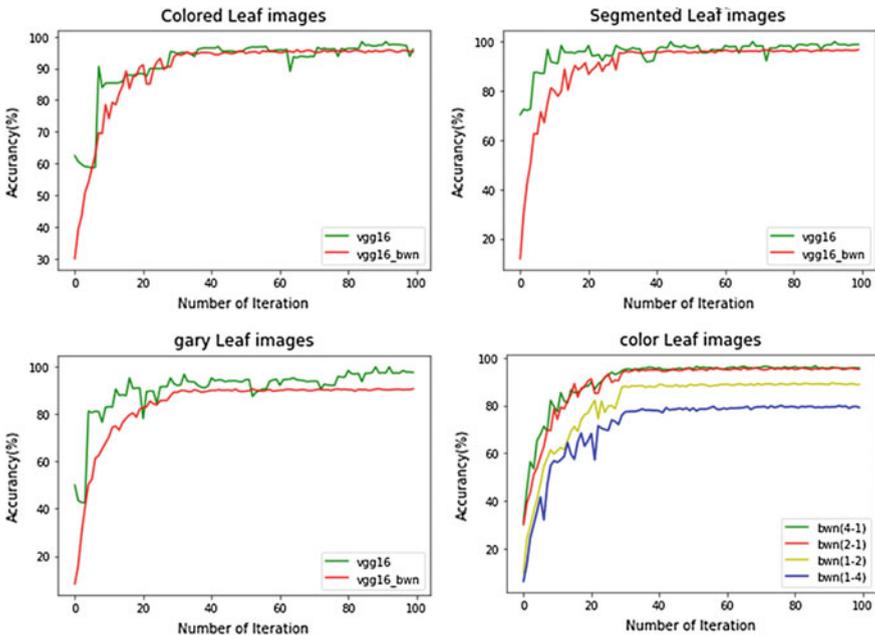


Fig. 2. Line chart of experimental results

In this paper, it is shown in Table 1 that the convolutional neural network is more suitable for plant detection compared with the traditional methods. Most of the traditional methods rely on features of manual extraction but such features cannot fully reflect the diseases. The convolutional structures can extract features automatically as it has the ability to eliminate interference caused by noise. In this paper, softmax is used to classify leaves, and the average accuracy can reach 99.0% on segmented datasets.

**Table 1.** Comparison of experimental results from different methods

Identification methods	Average accuracy (%)
RBF recognition	83.3
K recognition	90.0
BP recognition	92.1
SVM recognition	91.1
CNN recognition	99.0

The VGG16 has a huge amount of float parameters, which can extract picture features more comprehensively. When the floating point parameters are binarized, the model loses part of the features, which makes the features blurred and reduces the expression ability of the model. From another point of view, it speeds up the calculation of the model. In the experiment, the average recognition accuracy of the full-precision model is slightly higher than that of the binarized model. The former can reach 99.0%, and the latter can reach 96.8%. In terms of time, the speed of forward transmission of the latter is 2.7 ms per picture, which is about twice as fast as the former. That is to say the binarized model gets faster speed by losing part of its accuracy (Table 2).

**Table 2.** Comparison of full-precision model and binarized model

Neural networks	Segmented images	
	Classification accuracy (%)	Transmission rate (ms)
Full-precision network	99.0	2.7
Binarized network	96.8	1.5

In this paper, three kinds of datasets are chosen. It can be seen from Table 3 that the model performs best under the segmented dataset. The average accuracy can reach 96.8%. But the accuracy of the color dataset is 0.9% lower than the segmented dataset, which indicates that the model pays more attention to the features of leaf diseases. The accuracy of grayscale dataset is reduced by 4.7% compared with the color dataset, which means that in addition to some physical features such as contours and veins, color can also have a positive effect on the plant identification.

**Table 3.** Comparison of experimental results from different datasets

Network types	Datasets (accuracy)		
	Color (%)	Segmented (%)	Gary (%)
Binarized networks	95.9	96.8	91.2

Not all the data can be used for training. In the experiment, the overexposed images are generated due to the randomness of the parameters, which directly covered the features of texture and contour. The model could not extract useful features, so the accuracy is not high. The overexposed images should be deleted.

## 6.4 Conclusion

In this paper, the PlantVillage dataset and extended dataset are selected, and the binarized model is used to identify plant diseases. The experiment shows that the full-precision model and the binarized model both have the best performance under the segmented dataset, which can reach high accuracy and spend less time. Comparing the three datasets, the physical features such as leaf outline and plant meridians, the features of color, and background also have a great impact on the model. Comparing the convolutional models with the traditional models, the former can extract more details for training, also it can adapt to a complex environment.

The binarized model can work well in experiment, and the calculation speed is twice as fast as the full-precision model, which provides a basis for plant disease research.

## References

1. Cao X, Zhou Y et al (2016) Progress in monitoring and forecasting of plant diseases. *J Plant Prot* 3:1–7
2. Zhang R, Wang Y (2016) Research on machine learning with algorithm and development. *J Commun Univ China (Sci Technol)* 23(2):10–18
3. Kan J, Wang Y, Yang X et al (2010) Plant recognition method based on leaf images. *Sci Technol Rev* 28(23):81–85
4. Tan F, Ma X (2009) The identification of plant diseases based on leaf images. *J Agric Mech Res* 31(6):41–43
5. Zhang N, Liu W (2013) Plant leaf recognition method based on clonal selection algorithm and K nearest neighbor. *J Comput Appl* 33(07):2009–2013
6. Wang L, Huai Y, Peng Y (2007) Method of identification of foliage from plants based on extraction of multiple features of leaf images. *J Beijing For Univ* 165:535–547
7. Dyrmann M, Karstoft H, Midtby HS (2016) Plant species classification using deep convolutional neural network. *Biosyst Eng* 151:72–80
8. Mohanty SP, Hughes DP, Salathé M (2016) Using deep learning for image-based plant disease detection. *Front Plant Sci* 7:1419
9. Lee SH, Chan CS, Mayo SJ et al (2017) How deep learning extracts and learns leaf features for plant classification. *Pattern Recogn* 71:1–13