

: 2019-03-05; 2019-04-19; 2019-05-17
(61725204, 31471198) ()BM2016034) (:)

(phenomics) (phenotype) (phenome)

[1], [2,3], [4]

91

70%

2050

Yao [9] , 87.5% Wang [15]
() ,

,
,
1.3 ,

. Singh [10] , [16]

[11] , [17]

[12]

BP , [18~26]

Clément [27]

1.2 RGB HIS L*a*b*

Otsu , [21]

Otsu K-

means , Mohan [28]

SIFT , K (K-nearest neighbors, KNN) (support vector machine, SVM)

. LemnaTec (https://www.lemnatec.com/applications/case-studies/)

(coloro-occurrence matrix, CCM)

Burks [13] [29]

CCM Hussin [14] (scale- SIFT

invariant feature transform, SIFT)

- [30] Liu (radial function, RBF) 85%,
(principal component analysis, PCA)
- Journaux [42]
- PCA (principal components, 4%, Cointault [39]
PCs), PCS RBF Liu [31]
PCA (learning, Fernandez-
LVQ) PCA Gallego [43]
LVQ, [37]
- SVM
- Sadeghi-Tehran [44]
SIFT of visual words, SVM
BoVW)
- [45]
- [46~54] [46,51,52,54,55]
[52]
[46,48,50,56,57]
- Wang [58]
- [32,33]
- HSV
- 480 -3.2%,
670 1.2%.
Germain [24]
Linker [59]
- [35~39] [36~41]
- Cointault [39]

2

2014. VGGNet^[65]

ILSVRC

GoogleNet^[66] ILSVRC

2015 ResNet^[67]

(152

)

SegNet^[68]

R-CNN^[70] Fast-RCNN^[71] Fast-FCNN

ter R-CNN^[72] CNN

CNN 1

(end-to-end)

CNN

CNN(1).

1959 Hubel and Wiesel^[60]

1962

1984 Fukushima^[61] (Neocognitron)

1998 Lecun^[62] LeNet-5

2012 Hinton and Salakhutdinov^[63] AlexNet

ImageNet scale visual recognition challenge(ILSVRC)

ImageNet

ensorFlow, TCaffe,



1 ()

Figure 1 Architecture of convolutional neural networks (color online)

Keras, Torch, PyTorch, Theano . : (multi-layer perceptron, MLP)

TensorFlow Theano Caffe , ,
Keras Torch Lua, PyTorch Python. 99.6%,
 , SVM MLP ,
 ,
 . [79,80]

3

3.1

, , CNN
 , ,
 [73,74] ,
 Grinblat [81]
 [73,75] ,
 ,
 CNN ,
 [80]
 1. ,
 CNN
 ,
 5 . (96.9%
 92.6% 0.2%,
 0.2%)
 ,
 Lee [78] 44
 MalayaKew , PlantCLEF .
 AlexNet ,
 , .

1

Table 1 Commonly used plant detection software and tools

LeafSnap ^[76]	http://leafsnap.com	;	LeafSnap	185	,
			30000		
Pl@ntNet ^[77]	http://identify.plantnet-project.org	APP	,	;	
Microsoft garage s flower recognition	https://www.microsoft.com/en-us/garage/profiles/flower-recognition/		IOS		,
	http://hbl.nongbangzhu.cn				3000
	http://stu.iplant.cn/web		5000	;	
	http://www.xingseapp.com				1000
			4000	;	
Garden answers	http://www.gardenanswers.com		2	;	API
. 2016		1000	ResNet		
	(10 K)	1	26
^[82] . 2017					
10000	1.1 MB				
			(encyclope-		~40% ^[86]
dia of life, EoL)					
^[83] . 2016			Dyrmann ^[87]		CNN
VGG, ResNet, AlexNet				22	10413
		CNN			
				86.2%	
				6	
2017					
Lasseck ^[84]		GoogLeNet	Re-		
sNeXT		, 2017	PlantCLEF		
					97%
		Sun			
^[85]				10000	
100		BJFU100			Potena
(http://pan.baidu.com/s/1jILsypS		^[88]		
					(ground-truth)

cles, UGV) (RGB+NIR) RGB-NIR ,

, CNN , , ,

RGB+NIR ,

(normal difference vegetation index, ,

NDVI) .

, , ,

NDVI , CNN .

, , 96.7% .

, NDVI ,

, CNN ,

, Sa [91] .

, 96% .

, s 3 GPS

23 , ,

0.99 98.3% .

Milioto , [89]

RGB , ,

RGB 1 1 , ,

RGB 14 Segnet , ,

RGB RGB+NIR

3.2

Hz, 20 ,

, [29] . () .

, , ,

, () .

Lottes [90] () .

FCN , , () .

, ,

(.) (2015), , Mo- . , hanty [92] PlantVillage , , Mohanty [92] . PlantVillage 14 26 AlexNet GoogLeNet, - Brahimi Fuentes [100] [93] AlexNet GoogleNet, 9 Amara [94] Faster R-CNN, SSD R-FCN, (ResNet-101, VGG, LeNet () , (1) : (2) ; Oppenheim Shani [95] () (3) ; (4) ; VGG (5) ; , , , () () . ang W [101] VGG-16 VGG-16 V4, VGG-16, DenseNets-121 ResNet-50 , 1438 , Ramcharan . Dense- , [102] MobileNet-SSD Nets Den- , 99.75% , Picon [103] ResNet-50 Liu , ILSVRC15 [97] AlexNet GoogLeNet AlexNet , , pooling Inception , Kawasaki [98] AlexNet, CNN 94.5% , Fujita [99] .

Madec ^[107]

2.

3.3

aSelNet ^[108]

-RCNN

(relative root mean-squared error, rRMSE) 6%, Faster-RCNN

^[105]

Pound ^[106]

ki ^[109]

Kuwata . Shibasa-

52001~2010

(enhanced vegetation index, EVI)

Caffe

SVM

0.81.

Kuwata . Shibasaki

You ^[110]

CNN

LSTM

95.91%

99.66%

Pound ^[106]

Table 2 Comparison of deep learning methods in automatic diagnosis of crop diseases

PlantVillage 14 54306	26 1921+1	- ;	AlexNet GoogLeNetRGB	GoogLeNet; PlantVillage score: 99.34%; 1 31.4% 2: 31.69%	F1 Mohanty [92]
PlantVillage 14828	9 400	- ;	AlexNet GoogLeNet dropout VGG	; 99.18% SVM	Brahimi [93]
PlantVillage 3700	3700 800	- ;	LeNet RGB	96% 99.72%	Oppenheim Amara [94]
5000	9	- ;	Faster R-CNN, SSD R-FCN Alex-; Net, ZFNet, VGG-16, GoogLeNet ResNet	; Faster R-CNN+VGG-16, mean AP0.8306	Fuentes [100]
PlantVillage 1053	2086 4	- ;	VGG16, VGG19, Inception-v3 ResNet AlexNet GoogLeNet, VGG, SVM, BP	ANN VGG16 90.4%	Wang [101]
2415	2415	- ;	MobileNet-SSD	F1 score: 0.79, 0.26/0.54, 0.25/0.48	Ramcharan [102]
8178	8178	- ;	ResNet-50	BAC 0.87	Picon [103]

Chen [111] label.ag , , CNN FCN [68] 0.826. , (3). , Pothen Nuske [112] Rahnmooonfar Sheppard [113] 4 Incep- tion-ResNet-A [114] reduction Xavier 90% s, 1 Bargoti Underwood [115] 8000 [116] CNN

:

3

Table 3 Comparison of deep learning methods in yield prediction

520				95.91%,		Pound	[106]
,	,			99.66%			
(CRU)							
MQDIS	hard threshold			RMSE	6.298	SVR	Kuwata saki
(EVI)	2001	(EVI)					[109]
2010							Shiba-
71							
21		SVG					
ag	label.			IoU		[112]	Chen
SVG				0.813, 0.838, L2			[111]
				13.8			
24000				10.5			
2400							
100				IncepRMSE	1.16,		Rahnemoonfar
				tion-ResNet-A			Sheppard
				RMSE	2.52	Inception-Re-sNet-A	[113]
8000							
				CNN			
1100				F1			Bargoti
				0.791			wood

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RNN

,

LSTM

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RNN, LSTM

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CNN

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A survey on deep-learning-based plant phenotype research in agriculture

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Plant phenotype refers to measurable traits of plants, which acts as an observable proxy between gene expression and environmental impact, and is also an important determinant for the yield, quality and stress resistance characteristics of crops. Most of the plant phenotypes can be acquired by digital imaging techniques and processed by image processing algorithms. In recent years, the rapid development of genomics advances the study of plant phenotyping in many aspects, especially in terms of high-precision and high-throughput. Traditional plant phenotype research cannot meet these requirements and revolutions are in urgent need. As a breakthrough in computer science, the emergence of deep learning approaches significantly expands the capability of traditional image processing. For instance, state-of-the-art results in identification and segmentation tasks have been achieved by deep-learning-based methods and the records are continually improved by their variants. It is an interesting topic to study how to incorporate deep-learning techniques into plant phenotype research, and various impactful methods have been proposed in the past few years. The objective of this survey is to provide an overview of the current progress of deep-learning-based plant phenotype research in agriculture. In this survey, we elaborate the work from four different aspects, (i) plant morphology and physiological information extraction, (ii) plant identification and weed detection, (iii) pest detection, and (iv) yield prediction. We also analyze the pros and cons of these methods compared to traditional approaches. The potential future trends of plant phenotyping research are discussed at the end of this survey.

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