Study on Plant Diseases and Insert Recognition Based on Deep Le
*Abstract***—Distinguishing between different diseases and the members have different
Abstract—Distinguishing between different diseases and rechnology av** IAENG International Journal of Computer Science

Study on Plant Diseases and Insect Pests

Recognition Based on Deep Learning

X.Q. Yu, X.R. Yao, and J. Gao

members have different levels of experience and Recognition Based on Deep Learning rnational Journal of Computer Science

mt Diseases and Insect Pests

1 Based on Deep Learning

X.Q. Yu, X.R. Yao, and J. Gao

members have different levels of experienc

t diseases and technology available to them. Hence,

insect pests that affect maize crops is difficult. Therefore, in this
insect pests that affect maize crops is difficult. Therefore, in this
*Abstract***—Distinguishing between different diseases and technology available Study Of THATTE DISCUSS AND THIST**
 SECOGNOMITION BASED ON DEEP LEA
 S.Q. Yu, X.R. Yao, and J. Gao

members have different

insect pest that affect maize disease resposits difficult. Therefore, in this

study, a maize **Recognition Based on Deep**
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 thestract—Distinguishing between different diseases and technology avail

insect pests that affect maize crops is difficult. Therefore, in this

study, a maize **Recognition Based on Deep Le**
 N.Q. Yu, X.R. Yao, and J. Gao
 members have different
 network models are these models in the identification
 network, VGC16, and ResNetO deep convolutional
 neural network models. **Example 19 and 19** X.Q. Yu, X.R. Yao, and J. Gao
 distract—Distinguishing between different diseases and

incombers have different

insect pests that affect maize crops is difficult. Therefore, in this

study, a maize disease and pest data X.Q. Yu, X.R. Yao, and J. Gao

members have diffe
 the these

insect pests that affect maize crops is difficult. Therefore, in this

study, a maize disease and pest database was established to

reain the AlexNet, VGG16, A.Q. Yu, X.R. Yao, and J. Gao
 abstract—Distinguishing between different diseases and technology available

insect pests that affect maize crops is difficult. Therefore, in this

study, a maize disease and pest database *respectively***. Compared with the represention of resultion and accurate technique for sets that affect maize compared with the density, a maize disease and pest database was established to invitable in the identification** *recognition* accuracy of the proposed method was superiorization accuracy of the proposed method was superiorismic discussi *result the text* **much the strong in the strong strong and the strong strong is different insect posts that affect maize crops is difficult. Therefore, in this inevitable in the identificatio strong is a state disease and** *Abstract*—Distinguishing between different diseases and technology availables in the study, a maize disease and pest database was established to train the AlexNet, VGG16, and ResNet50 deep convolutional in judgement is me **pests.** ect pests that affect maize crops is difficult. I herefore, in this

inevitable in the identify

in judgement is made,

in the AlexNet, VGG16, and ResNet50 deep convolutional

ural network models. After training, these mod study, a malze usease and pest database was estable
train the AlexNet, VGG16, and ResNet50 deep conv
neural network models. After training, these models w
to identify different types of diseases via the identifi
disease in GG16, and ResNet50 deep convolutional

I.e. After training, these models were used

See ypes of diseases via the identification of

area images. The test results showed that

gnition accuracies of the AlexNet, VGG16,

s we

respectively. Compared with the traditional method, the tremendously. Furtherm

resoult provides a strong basis for pest control work via disciplines, including

real-time and accurate technique for identifying agricultur recognition accuracy of the proposed method was superior. This disciplines, including compute

real-time and accurate technique for identifying agricultural

real-time and accurate technique for identifying agricultural

t result provides a strong basis for pest control work via a computers to "see" in order to according a recultive and accurate technique for identifying agricultural improved the accuracy of object denotes, pests, identifica From and actual exemption of commissumes and actual exemption of deep neurring and the development of deep neurring the actual information systems. The automatic recognition of diseases in images contributed in the materia *Index Terms*—deep learning, crops, convolutional neural

metworks, pests, identification

I. INTRODUCTION diseases in images con

diseases in mages controllingent recognition
 \bf{A} griculture is the material basis for networks, pests, identification

I. INTRODUCTION

integrals of the progress of intelli 1. INTRODUCTION

1 1. INTRODUCTION

1. INTRODUCTION

diseases and the pred

human society, and it is particularly significant to

China, which has a rich history extending back thousands

These favorable charace

of years. The development of **A** griculture is the material basis for the progress of intelligent recognition capabili
human society, and it is particularly significant to networks are much faster than m
China, which has a rich history extending back **Thuman society, and it is particularly significant to** networks are much faster tha

ina, which has a rich history extending back thousands These favorable characteristic

years. The development of agricultural modernizat China, which has a rich history extending back thousands

of years. The development of agricultural modemization is manual judgement in the domarked by water conservation, information technology, Continuous improvement in of years. The development of agricultural modernization is manual judgement in the domarked by water conservation, information technology, Continuous improvement in and mechanization [1], which are essential factors for re marked by water conservation, information technology,

and mechanization [1], which are essential factors for

recognition of crop pests a

reforming traditional agriculture. However, in China, a

substantial amount of ava and mechanization [1], which are essential factors for

reforming traditional agriculture. However, in China, a

uchgesterm and stable developments

substantial amount of available information is not being

and green agric

reforming traditional agriculture. However, in China, a long-term and stable developm
substantial amount of available information is not being and green agriculture [13-16].
utilized to advance the country's agricultural c substantial amount of available information is not being

utilized to advance the country's agricultural capabilities. In this study, a convolutional

Therefore, to transform, upgrade, and develop China's based on deep lea utilized to advance the country's agricultural capabilities. In this study, a convolution
Therefore, to transform, upgrade, and develop China's based on deep learning is j
agriculture, it is important to vigorously develop Trustal distribution of the fruit and leaves of crops). This employed in the method requires skilled technicians or agricultural experts employed in the method requires skilled technicians or agricultural experts processi detected using artificial pest identification methods (i.e., usserious includived

manual observation of the fruit and leaves of crops). This employed in the me

method requires skilled technicians or agricultural experts
 manual observation of the fruit and leaves of crops). This employed in the
method requires skilled technicians or agricultural experts
who rely on past experience to perform a large number of network model.
tedious and re method requires skilled technicians or agricultural experts

who rely on past experience to perform a large number of

tedious and repetitive checks, measurements, and the network model. Sect

statistical calculations. How method requires skince technicials of agricultural experies

who rely on past experience to perform a large number of

tedious and repetitive checks, measurements, and

statistical calculations. However, this approach has no rely on past experience to perform a large number of

dious and repetitive checks, measurements, and the network model. I

distictal calculations. However, this approach has a optimizing and refini

mber of inherent sh

Ses and Insect Pests

on Deep Learning

ao, and J. Gao

members have different levels of experience and

technology available to them. Hence, human error is

inevitable in the identification process, and once a mistake

in technology available to them. Hence, human error is **isomage in the identification process, and once a mistake and technology** available to them. Hence, human error is inevitable in the identification process, and once a mistake in judgement is made, it may result in signif **is sexternal in the significant is made to the significant in the significant is made, and J. Gao**
members have different levels of experience and technology available to them. Hence, human error is
inevitable in the iden **SECONDE SECONDE SECONDE SECONDE SECONDE SECOND**
 SECONDE SECONDE SEC ON Deep Learning

ao, and J. Gao

members have different levels of experience and

technology available to them. Hence, human error is

inevitable in the identification process, and once a mistake

in judgement is made, **On Deep Learning**
ao, and J. Gao
members have different levels of experience and
technology available to them. Hence, human error is
inevitable in the identification process, and once a mistake
in judgement is made, it ma and J. Gao

I. The different levels of experience and

thnology available to them. Hence, human error is

evitable in the identification process, and once a mistake

judgement is made, it may result in significant errors.
 ao, and J. Gao
members have different levels of experience and
technology available to them. Hence, human error is
inevitable in the identification process, and once a mistake
in judgement is made, it may result in signifi ao, and J. Gao
members have different levels of experience and
technology available to them. Hence, human error is
inevitable in the identification process, and once a mistake
in judgement is made, it may result in signifi

an entwork models. After training, these models were used

Second, effectively and accurate

existeric types of diseases via the identification of

existering manual mediations are using traditional manual mediations

are e indetacts in local images. The eta-
exist and images. The test results showed that pests may escape during manual me
seinted in local images. The test results showed that
didation set recognition accuracies of the AlexNe disease macetors in local magnes. In etert results inword mat

the validation set recognition accuracies of the AlexNet, VGG16,

the recording and ResNet50 models were 86.98%, 87.70%, and 85.98%,

recording a recording th and ResNet50 models were 86.98%, 87.70%, and 85.98%,

and 85.98%, the recent vears, deep le

respectively. Compared with the traditional method, the

recent of accuracy of the proposed method was superior. This disciplines members have different levels of experience and
technology available to them. Hence, human error is
inevitable in the identification process, and once a mistake
in judgement is made, it may result in significant errors.
Se members have different levels of experience and
technology available to them. Hence, human error is
inevitable in the identification process, and once a mistake
in judgement is made, it may result in significant errors.
Se members have different levels of experience and
technology available to them. Hence, human error is
inevitable in the identification process, and once a mistake
in judgement is made, it may result in significant errors.
Se technology available to them. Hence, human error is
inevitable in the identification process, and once a mistake
in judgement is made, it may result in significant errors.
Second, effectively and accurately calculating the inevitable in the identification process, and once a mistake
in judgement is made, it may result in significant errors.
Second, effectively and accurately calculating the disease
area using traditional manual methods is di in judgement is made, it may result in significant errors.
Second, effectively and accurately calculating the disease
area using traditional manual methods is difficult. Third,
pests may escape during manual counting.
In Second, effectively and accurately calculating the disease
area using traditional manual methods is difficult. Third,
pests may escape during manual counting.
In recent years, deep learning has advanced
tremendously. Furt area using traditional manual methods is difficult. Third,
pests may escape during manual counting.
In recent years, deep learning has advanced
tremendously. Furthermore, its research involves multiple
disciplines, includi pests may escape during manual counting.
In recent years, deep learning has advanced
tremendously. Furthermore, its research involves multiple
disciplines, including computer vision, which enables
computers to "see" in ord In recent years, deep learning has advanced
tremendously. Furthermore, its research involves multiple
disciplines, including computer vision, which enables
computers to "see" in order to acquire data. Additionally,
the de tremendously. Furthermore, its research involves multiple
disciplines, including computer vision, which enables
computers to "see" in order to acquire data. Additionally,
the development of deep neural networks has signifi disciplines, including computer vision, which enables
computers to "see" in order to acquire data. Additionally,
the development of deep neural networks has significantly
improved the accuracy of object detection and recog computers to "see" in order to acquire data. Additionally,
the development of deep neural networks has significantly
improved the accuracy of object detection and recognition
systems. The automatic recognition of crop pest the development of deep neural networks has significantly
improved the accuracy of object detection and recognition
systems. The automatic recognition of crop pests and
diseases in images contributes to the diagnosis of cr proved the accuracy of object detection and recognition
stems. The automatic recognition of crop pests and
seases in images contributes to the diagnosis of crop
seases and the predictions of crop growth, as the
elligent re systems. The automatic recognition of crop pests and
diseases in images contributes to the diagnosis of crop
diseases and the predictions of crop growth, as the
intelligent recognition capabilities of deep neural
networks diseases in images contributes to the diagnosis of crop
diseases and the predictions of crop growth, as the
intelligent recognition capabilities of deep neural
networks are much faster than manual detection [8-12].
These f diseases and the predictions of crop growth, as the intelligent recognition capabilities of deep neural networks are much faster than manual detection [8-12]. These favorable characteristics can decrease reliance on manual intelligent recognition capabilities of deep ne
networks are much faster than manual detection [8-
These favorable characteristics can decrease reliance
manual judgement in the detection of crop disea
Continuous improvemen tworks are much faster than manual detection [8-12].

ese favorable characteristics can decrease reliance on

mual judgement in the detection of crop diseases.

Infinitions improvement in the automatic visual

cognition of These favorable characteristics can decrease reliance on
manual judgement in the detection of crop diseases.
Continuous improvement in the automatic visual
recognition of crop pests and diseases will promote the
long-term

manual judgement in the detection of crop diseases.
Continuous improvement in the automatic visual
recognition of crop pests and diseases will promote the
long-term and stable development of accurate, efficient,
and green Continuous improvement in the automatic visual
recognition of crop pests and diseases will promote the
long-term and stable development of accurate, efficient,
and green agriculture [13-16].
In this study, a convolutional recognition of crop pests and diseases will promote the
long-term and stable development of accurate, efficient,
and green agriculture [13-16].
In this study, a convolutional neural network model
based on deep learning is long-term and stable development of accurate, efficient,
and green agriculture [13-16].
In this study, a convolutional neural network model
based on deep learning is proposed to automatically
identify maize pests and disea and green agriculture [13-16].

In this study, a convolutional neural network model

based on deep learning is proposed to automatically

identify maize pests and diseases. Different network

models are tested in comparati In this study, a convolutional neural network model
based on deep learning is proposed to automatically
identify maize pests and diseases. Different network
models are tested in comparative experiments to optimize
the reco based on deep learning is proposed to automatically
identify maize pests and diseases. Different network
models are tested in comparative experiments to optimize
the recognition accuracy.
The rest of this paper is organize In Comparative experiments to optimize
ccuracy.
Sepaper is organized as follows. Section II
Involutional neural network (CNN) models
e method. Section III outlines the data
edure, and Section IV presents the final
Section recognition accuracy.
The rest of this paper is organized as follows. Section II
scribes the convolutional neural network (CNN) models
ployed in the method. Section III outlines the data
ocessing procedure, and Section IV The rest of this paper is organized as follows. Section II
describes the convolutional neural network (CNN) models
employed in the method. Section III outlines the data
processing procedure, and Section IV presents the fin describes the convolutional neural network (CNN) models
employed in the method. Section III outlines the data
processing procedure, and Section IV presents the final
network model. Section V details the tests performed on
 employed in the method. Section III ou
processing procedure, and Section IV pre
network model. Section V details the test:
the network model. In Section VI, the pro
optimizing and refining the network mode
Section VII disc EXTRED THE SECTION V details the tests performed on
 A. AlexNet model. In Section VI, the process of further

potimizing and refining the network model is explained.
 A. AlexNet MIII contains the conclusions of the stu Exercise and refining the network model is explained.

timizing and refining the network model is explained.

ction VII discusses the interpretation of the results.

nally, Section VIII contains the conclusions of the stud

optimizing and refining the network model is explained.
Section VII discusses the interpretation of the results.
Finally, Section VIII contains the conclusions of the study.
II. NETWORK MODELING
In this study, a CNN was us

tedious and repetitive checks, measurements, and the network model. I
statistical calculations. However, this approach has a optimizing and refin
number of inherent shortcomings. First, different staff Section VII discusse France Entertainmum is the Mortocomium of inherent shortcomings. First, different number of inherent shortcomings. First, different was supported by the Institute for Big Data and Visual Computing partially supported this Itsucar carculations. However, time approach has a community and community more of inherent shortcomings. First, different staff Section VII discuss Finally, Section VII and the Section VII and the Section VII and the Sect number of inherent shortcomings. First, different

Manuscript received March 20, 2024; revised August 24, 2024. Thi

was supported by the Institute for Big Data and Visual Computing,

partially supported this research thro Finally, Section VII

Supported by the Institute for Big Data and Visual Computing, which

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tially supported this research through the Key Research and De Manuscript received March 20, 2024; revised August 24, 20

was supported by the Institute for Big Data and Visual Compartially supported this research through the Key Research and

Project of Shanxi Province under Grant 20

 28×28
Compared to traditional convolutional neural netwo
its superiority is primarily manifested in the follow
aspects: data augmentation, ReLU activation functi
local response normalization, dropout, overlap pooli
an Compared to traditional convolutional neura
its superiority is primarily manifested in the
aspects: data augmentation, ReLU activation
local response normalization, dropout, overla
and multi-GPU parallelism [17]. The relev 28 × 28 × 28 × 256 \overline{B} softmax

112 × 112 × 64

Fig. 2. Network architecture of VGG16.

Compared to traditional convolutional neural networks, feature extraction, and the

spects: data augmentation, ReLU activation f Example 12 and Exploration and the Fig. 2. Network architecture of VGG16.

Compared to traditional convolutional neural networks, feature extraction, and this superiority is primarily manifested in the following used to p Fig. 2. Network architecture of VGGI

Compared to traditional convolutional neural networks, feature extrits

its superiority is primarily manifested in the following

used to pro

approximation, ReLU activation function, Compared to traditional convolutional neural networks,

seature extraction, and the

superiority is primarily manifested in the following

the superiority is primarily manifested in the following

density and the second en Compared to traditional convolutional neural networks,

the state extraction, and the R

its superiority is primarily manifested in the following

used to process the image ne

apronse normalization, dropout, overlap pool its superiority is primarily manifested in the following
aspects: data augmentation, ReLU activation function,
local response normalization, dropout, overlap pooling,
and multi-GPU parallelism [17]. The relevant features o aspects: data augmentation, ReLU activation functional response normalization, dropout, overlap poor and multi-GPU parallelism [17]. The relevant feature AlexNet are as follows.
(1)Data enhancement. AlexNet's data enhancem

(2)Dropout. and multi-GPU parallelism [17]. The relevant features of

AlexNet are as follows.

(1)Data enhancement.

AlexNet's data enhancement methods include

first fully connected lay

horizontal dipping, random cropping, panning
 AlexNet are as follows.

(1)Data enhancement.

MexNet's data enhancement methods include

horizontal flipping, random cropping, panning pooling layer are

transformation, and color and light transformation.

Cloppout ensur AlexNet's data enhancement meth
horizontal flipping, random croppin
transformation, and color and light transfor
(2)Dropout.
Dropout ensures that the neuron's outpu
AlexNet chooses a probability of 0.5. This
designed to pr

ansformation, and color and light transformation.
 P. Dropout ensures that the neuron's output is zero when

lexNet chooses a probability of 0.5. This technique was

sesigned to prevent overfitting.
 B. V. Activation f External to the network structure of VGG16 is shown in Fig. 2.

the convention of the network structure of VGG16 is shown in Fig. 2.

the convention of the conventions of the activation function. With this

ReLU is used f Expression:

Dropout ensures that the neuron's output is zero when

AlexNet chooses a probability of 0.5. This technique was

the derived and transmitted

designed to prevent overfitting.

(3) Activation function.

(3) Ac Example the convolutional convolutional operation and the convolutional space of the convolution function.

AlexNet chooses a probability of 0.5. This technique was the derived and trace and the designed to prevent overfi Alternative chooses a procedure of designed to prevent overfitting.

designed to prevent overfitting.

(3) Activation function. With this

approach, faster learning is possible, which is beneficial

for training complex m Equal to previous the term of the integral of the magnetic properties of the material and the network function.

(3) Activation function. Setter learning is possible, which is beneficial for training complex models using EVEN is used for the activation function. With this
approach, faster learning is possible, which is beneficial
for training complex models using large datasets.
Because of gradient vanis
for training complex models using

■ convolution+ReLU

■ max pooling

■ fully connected+ReLU

domax

domax

domax

domax

domay softmax

domay is concerned the ReLU activation function is

used to process the image nonlinearly. Each part of the max pooling
fully connected+ReLU
softmax
softmax
divergence of VGG16.
ture extraction, and the ReLU activation function is
divergence of the proved by a pooling layer, which
the performing a full join operation with the
tu of the settled Hell and the Rell activation function is
the of VGG16.
feature extraction, and the Rell activation function is
used to process the image nonlinearly. Each part of the
convolutional layer is followed by a poo

al response normalization, dropout, overlap pooling,

an be used to carry out the

imulti-GPU parallelism [17]. The relevant features of
 $\frac{1}{2}$ features extracted from the c
 $\frac{1}{2}$ can the achievance activation.
 Data enhancement.

Finally, after performing a filterational dipping, random cropping, panning first fully connected layer, the rizontal flipping, random cropping, panning pooling layer are tiled into a obtain a 1×4006 on poolinization, and the ReLU activation function is
feature extraction, and the ReLU activation function is
used to process the image nonlinearly. Each part of the
convolutional layer is followed by a pooling layer, which
 obtain a 1×4096 one-dimensional vector can
be derived a 1×40 one-dimensional alger is followed by a pooling layer, which
can be used to carry out the maximum pooling of the
features extracted from the convolutional layer (cture of VGG16.

feature extraction, and the ReLU activation function is

used to process the image nonlinearly. Each part of the

convolutional layer is followed by a pooling layer, which

can be used to carry out the ma feature extraction, and the ReLU activation function is
used to process the image nonlinearly. Each part of the
convolutional layer is followed by a pooling layer, which
can be used to carry out the maximum pooling of the feature extraction, and the ReLU activation function is
used to process the image nonlinearly. Each part of the
convolutional layer is followed by a pooling layer, which
can be used to carry out the maximum pooling of the used to process the image nonlinearly. Each part of the
convolutional layer is followed by a pooling layer, which
can be used to carry out the maximum pooling of the
features extracted from the convolutional layer (i.e., 1000. ratures extracted from the convolutional layer (i.e., to
ownscale the features) [18].
Finally, after performing a full join operation with the
rst fully connected layer, the output features of the fifth
pooling layer are t wnscale the features) [18].

When the teatures) [18].

Finally, after performing a full join operation with the

st fully connected layer, the output features of the fifth

oling layer are tiled into a one-dimensional vec Finally, after performing a full join operation with the
first fully connected layer, the output features of the fifth
pooling layer are tiled into a one-dimensional vector to
obtain a 1×4096 one-dimensional vector, which First fully connected layer, the output features of the fifth
pooling layer are tiled into a one-dimensional vector to
obtain a 1×4096 one-dimensional vector, which is used to
perform a full join operation with the second pooling layer are tiled into a one-dimensional vector to
obtain a 1×4096 one-dimensional vector, which is used to
perform a full join operation with the second fully
connected layer. Then, a 1×4 one-dimensional vector can

poting in year act into the three interests of the network obtain a 1×4096 one-dimensional vector, which is used to perform a full join operation with the second fully connected layer. Then, a 1×4 one-dimensional vector c become a final in operation with the second fully
perform a full join operation with the second fully
connected layer. Then, a 1×4 one-dimensional vector can
be derived and transmitted to the Softmax layer for
classifi superior. mected injer. Then, a 1^{7,6} one dimensional vector can derived and transmitted to the Softmax layer for derived and transmitted to the Softmax layer for 0.00.

2. *ResNet50 network model*

Because of gradient vanishing an be derived and annihinted to the bothmax hayer for
classification, where the number of classifications is
1000.
C. ResNet50 network model
Because of gradient vanishing and explosion, very
deep networks are difficult to tra Favore in the manner of enablements is
1000.
C. ResNet50 network model
Because of gradient vanishing and explosion, very
deep networks are difficult to train; therefore, the idea of
residual learning, which consists of mul C. ResNet50 network model
Because of gradient vanishing and explosion, very
deep networks are difficult to train; therefore, the idea of
residual learning, which consists of multiple residual
blocks, has been developed [19

Comv5_x

Comv5_x
 7×7

Comv5_x
 7×7
 1×1

Average Pool, 1000-d fc,

Softmax

FLOPs

ELOPs

ELOPs

ELOPs

ELOPs

Softmax

Softmax

Softmax

(severe)

Suize rust

(severe)

IIS sheets

(severe)

IIS sheets

(sev Conv5_x
 $\frac{1}{2}$ 7 x 7
 $\frac{1}{2}$ Average Pool,1000-d fc,
 $\frac{1}{2}$ Maize grey Conv5_x
 $\frac{1}{x}$
 $\frac{1}{x}$

Average Pool,1000-d fc,

Softmax

The Construct the dataset required to train the

Construct the dataset required to train the

Construct the dataset required to train the

Construct the dat $^{1\times1}$
 $^{1\times1}$
 FLOPs
 $\begin{array}{c|c|c|c|c} \text{FLOPs} & 3.8 \times 10^9 & \text{Maize rust} & 115 \text{ sheets} & 38 \times 10^9 & \text{Maize rust} & 18 \times 10^9 & \text{Maize rust} & 559 \text{ sheets} & 18 \times 10^9 & \text{Maize rust} & 559 \text{ sheets} & 18 \times 10^9 & \text{Maize rust} & 559 \text{ sheets} & 18 \times 10^9 & \text{Maize next} & 559 \text{ sheets} & 18 \times 10^9 & \text{Maize must} & 559 \$ FLOPs

III. DATA PROCESSING

III. DATA PROCESSING

Construct the dataset required to train the

convolutional neural networks utilized in this study, we

primarily used images from the crop disease detection

competition Maize nut and Maize nut and Maize nut and S59 sheets

To construct the dataset required to train the

convolutional neural networks utilized in this study, we

primarily used images from the crop disease detection

competi III. DATA PROCESSING

construct the dataset required to train the

convolutional neural networks utilized in this study, we

primarily used images from the crop disease detection

competition of the AI Challenger 2018 eve To construct the dataset required to train the

convolutional neural networks utilized in this study, we

primarily used images from the crop disease detection

competition of the AI Challenger 2018 event and related

ima To construct the dataset required to train the

convolutional neural networks utilized in this study, we

primarily used images from the crop disease detection

images crawled using Baidul. According to statistics, the

i convolutional neural networks utilized in this study, we

primarily used images from the crop disease detection

images carveled using Baidu. According to statistics, the

images analyzed in AI Challenger's crop disease
 primarily used images from the crop disease detectic
competition of the AI Challenger 2018 event and relate
images crawled using Baidu. According to statistics, the
images analyzed in AI Challenger's crop disea
detection c

all of Computer Science
degrees of the same disease. Therefore, it was necessary to
select and optimize the dataset and to produce training,
verification, and test sets valuable for training [20-23]. The
ratio of the tra **all of Computer Science**
degrees of the same disease. Therefore, it was necessary to
select and optimize the dataset and to produce training,
verification, and test sets valuable for training [20-23]. The
ratio of the tra verification, and test sets sets sets valuable for training, verification, and test sets valuable for training [20-23]. The ratio of the training, verification, and test sets was set to 6:2:2, as shown in Table II.
TABLE I **ratio of Computer Science**
degrees of the same disease. Therefore, it was necessary to
select and optimize the dataset and to produce training,
verification, and test sets valuable for training [20-23]. The
ratio of the t **and of Computer Science**

degrees of the same disease. Therefore, it was necessary to

select and optimize the dataset and to produce training,

verification, and test sets valuable for training [20-23]. The

ratio of the **nce**

Se. Therefore, it was necessary to

dataset and to produce training,

valuable for training [20-23]. The

ification, and test sets was set to

I.

TABLE II

CATION OF DATASET

Number of Number of

^{559 sheets} 186 sheets

(general)

Maize rust

(severe)

332 sheets

110 sheets

111 sheets

111 sheets

virus disease

244 sheets

80 sheets

81 sheets

81 sheets

111 sheets

111 sheets

111 sheets

111 sheets

111 shee (general)

Maize rust

(severe)

332 sheets

110 sheets

111 sheets

Virus disease

244 sheets

80 sheets

81 sheets

111 she Maize rust

(severe) 332 sheets 110 sheets 111 sheets

Maize mosaic

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The images originated from different sources, and thus

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The images originated from different sources, and thus

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Solution Maize mosaic

The images originated from different sources, and thus

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The images originated from different sources, and thus

they may have had inconsistencies in resolution and

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consistent. To improve the classification accuracy, the
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the image to convert the grayscale map, cropping the
imag original image was processed by scaling the image to
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the image to convert the grayscale map, cropping the
image to a size of 224×224, and normalizing the values.
A co Equal length and width, rotating the image, segmenting
the image to convert the grayscale map, cropping the
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the image to convert the grayscale map, cropping the
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A comparison between the original and processed images image to a size of 224×224, and normalizing the values.
A comparison between the original and processed images
is shown in Fig. 4.
IV. NETWORK MODEL
The Pytorch deep learning framework was used to
build a CNN, and the thr magnetic and between the original and processed in
A comparison between the original and processed in
is shown in Fig. 4.
IV. NETWORK MODEL
The Pytorch deep learning framework was us
build a CNN, and the three network mode The Pytorch deep learning framework was used to idd a CNN, and the three network models (AlexNet, GG16, and ResNet50) were pre-trained using the image taset. The following network parameters were trialized: learning rate Function, in the loss in front of the Softmax layer is extended a CNN, and the three network models (AlexNet, VGG16, and ResNet50) were pre-trained using the image dataset. The following network parameters were initialize IV. NETWORK MODEL
The Pytorch deep learning framework was used to
build a CNN, and the three network models (AlexNet,
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dataset. The following network parameters were
in The Pytorch deep learning framework v
build a CNN, and the three network mode
VGG16, and ResNet50) were pre-trained usin
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and number of t and number of training piece θ ..., names = 25. The p
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data feedforward and forward propagation w
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ne image), fu training epochs = 25. The preprocessed

input into the pre-training network, and

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= 25. The preprocessed
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ropagation were used for
s the cross-entropy loss
nt of the Softmax layer is

$$
loss(x, label) = -w_{label} log \frac{e^{x label}}{\sum_{j=1}^{N} e^{x^j}} = w_{label} \left[-x_{label} + log \sum_{j=1}^{N} e^{x^j} \right] (x \in R^N), (1)
$$

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where $x \in R^N$ is the activation value without
is the dimension of x (which is called
dimension), label $\in [0, C-1]$ is a scalar c
to the labels, C is the number of classification
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sion of x (which is called the feature the AlexNet classifier are
bel $\in [0, C-1]$ is a scalar correspon **IAENG International Journal of Computer Scien**
where $x \in \mathbb{R}^N$ is the activation value without Softmax, N by perparameters and loss
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of dimension C that represents the weights

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mension), la where $x \in \mathbb{R}^N$ is the activation value without Softmax, N hyperpars

is the dimension of x (which is called the feature the Alex)

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number of classifications, and $w \in$ not need in

sign C that represents the weights

reprobabilistic output of the values
 $x(X_i) = \frac$ Eve R is the activation value without somitary, N in propriations and tossell the dimension of x (which is called the feature the AlexNet classifier are nension), label $\in [0, C - 1]$ is a scalar corresponding loss functi is the dimension of x (which is cancel the clearate the case of an interaction), label $\in [0, C - 1]$ is a scalar corresponding to the labels, C is the number of classifications, and $w \in$ not need to redefine the Softmax

$$
Softmax(X_i) = \frac{exp(X_i)}{\sum_j exp(X_i)}.
$$
 (2)

$$
J(W, b, aL, y) = -\sum_{k} y_k \ln a_k^{L}, \qquad (3)
$$

training sample is class *i*, then $y_i = 0$. Because can see the solution was considered by $f(W, b, a^L, y) = -\ln a_k^L$. The optimization and the caloring sample of classification is given by the labels. The probabilistic output to the labels, C is the number of classifications, and $w \in R^c$ is a vector of dimension C that represents the weights
of the labels. The probabilities upput of the The training results for
multiclassification is given by R^L is a vector of dimension C that represents the weights

of the labels. The probabilistic output of the

multiclassification is given by
 $Softmax(X_i) = \frac{exp(X_i)}{\sum_j exp(X_i)}$. (2) and 15. At epochs are shown in Fig. 5. What
 $Softmax(X_i$ of the labels. The probabilistic output
multiclassification is given by
 $Softmax(X_i) = \frac{exp(X_i)}{\sum_j exp(X_i)}$.
The log-likelihood function LogSoftmax is g
used for classification, as shown in
 $J(W, b, a^L, y) = -\sum_k y_k ln a_k^L$,
Where $\ln a_k$ is t tion, as shown in
 $(a^L, y) = -\sum_k y_k \ln a_k^L$, (3)

s the output element of the Softmax

value of y_k is 0 or 1. If the output of a

is class *i*, then $y_i = 1$ and the

ll have $y_i = 0$. Because each sample

ne class, it can a own in
 $=-\sum_k y_k ln a_k^L$, (3) subsequent

out element of the Softmax 0.86, with
 λ_i is 0 or 1. If the output of a
 i, then $y_i = 1$ and the
 $= 0$. Because each sample

it can also be simplified, as
 λ_i , y) = $- ln a_k^$ So J that $\lambda_i = \sum_j exp(X_i)$. (2) and 15. At epochs 16 and

The log-likelihood function LogSoftmax is generally the highest accuracy of 8 and for classification, as shown in $J(W, b, a^L, y) = -\sum_k y_k \ln a_k^L$. (3) subsequently oscil The log-likelihood function LogSoftmax is generally

used for classification, as shown in
 $J(W, b, a^L, y) = -\sum_k y_k \ln a_k^L$, (3)

where $\ln a_k$ is the output element of the Softmax

Where $\ln a_k$ is the output element of the Soft $J(W, b, a^L, y) = -\sum_k y_k \ln a_k^L$, (3) subsequently oscillated

where $\ln a_k$ is the output element of the Softmax

function and the value of y_k is 0 or 1. If the output of a

training sample is class *i*, then $y_i = 1$ and the
 Where $\ln a_k$ is the output element of
function and the value of y_k is 0 or 1. If th
training sample is class *i*, then $y_i = i$
remaining $j \neq i$ all have $y_i = 0$. Because
belongs to only one class, it can also be s
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$$
J(W, b, aL, y) = -\ln a_k^L.
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class *i*, then $y_i = 1$ and the
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 $y_i = 0$. Because each sample
class, it can also be simplified, as
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 $y_i = 0$. Because each sa belongs to only one class, it can also be simplifi-
indicated by
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The optimization algorithm uses stochastic gradescent with momentum (SGDM), which adds ine

the gradient descent. That is, if a slo $J(W, b, a^L, y) = -\ln a_k^L$. (4)

The optimization algorithm uses stochastic gradient

descent with momentum (SGDM), which adds inertia to

the gradient descent. That is, if a slope is steep, SGDM

uses inertia to descend faste The optimization algorithm uses stochastic gradient

scent with momentum (SGDM), which adds inertia to

e gradient descent. That is, if a slope is steep, SGDM

es inertia to descend faster, which introduces first-order
 The optimization algorithm uses such assumed that the executivity momentum (SGDM), which alds inertia to descend faster, which introduces first-order

signification (5) indicates that the direction of descent at

Equation

$$
g_t = \nabla f(w_l). \tag{5}
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the gradient descent. That is, if a slope is steep, SODM
uses inertia to descend faster, which introduces first-order
SGD momentum:
 $g_t = \nabla f(w_t)$. (5)
Equation (5) indicates that the direction of descent at
time t is dete

$$
n_t = \emptyset(g1, g2, \dots, g_t),
$$

\n
$$
n_t = \emptyset(g1, g2, \dots, g_t)
$$
 (6)

$$
v = \varphi(y_1, y_2, \dots, y_t). \tag{7}
$$

moment:

$$
\eta t = \frac{am_t}{\sqrt{vt}}.\tag{8}
$$

$$
wt + 1 = wt - \eta t. \tag{9}
$$

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hyperparameters and loss function between the layers of
the AlexNet classifier are presented in Table III. As the
loss function was CrossEntropyLoss, the output layer did
not need to redefine the **Example 18 Computer Science**
thyperparameters and loss function between the layers of
the AlexNet classifier are presented in Table III. As the
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and 15. At epochs 16 and 17, the validation set achieved subsequently oscillated between 0.32 and 0.33, and the accuracy of the training set oscillated between 0.85 and value without Softmax, N by
perparameters and loss function is called the feature the AlexNet classifier are presponsible in the AlexNet classifier are presponsible in the softman of classifications, and $w \in$ not need to and remained unchanged when

(2) and 15. At epochs 16 and 17,

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of the training set decreas
 a_k^L , (3) subsequently oscillated betwe

accuracy of the training set of

accur **The training results for Alexandria**
The transference experiment and loss function between the layers of
Exercise AlexNet classifier are presented in Table III. As the
ss function was CrossEntropyLoss, the output layer di **all of Computer Science**

hyperparameters and loss function between the layers of

the AlexNet classifier are presented in Table III. As the

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The trai myperparameters and loss function between the layers of
the AlexNet classifier are presented in Table III. As the
loss function was CrossEntropyLoss, the output layer did
not need to redefine the Softmax function.
The trai 5. When epoch=6, the loss value
ged slightly, continued to decline,
1 when the epoch was between 10
dd 17, the validation set achieved
86.69%. Similarly, the loss value
lecreased until epoch=10 and
between 0.32 and 0.33, a 15. At epochs 16 and 17, the validation set achieved
highest accuracy of 86.69%. Similarly, the loss value
the training set decreased until epoch=10 and
osequently oscillated between 0.32 and 0.33, and the
uracy of the tra

See the Will momentum (SODM), which also line the and second the second faster, which introduces first-order

Second-order momentum:
 $g_t = \nabla f(w_t)$. (5)

Equation (5) indicates that the direction of descent at

the curren ined by both the direction of the gradient

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also in each epoch (denoted as t):

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the Equation (5) indicates that the direction of descent at

ne *t* is determined by both the direction of descent

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the current moment and the direction of the descent

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arameter using (5).

Trst- and second-order momenta

gradient, via
 $\emptyset(g1, g2, ..., g_t)$, (6)
 $\emptyset(g1, g2, ..., g_t)$.
 $\emptyset(g1, g2, ..., g_t)$.
 $\emptyset(\emptyset, g2, ..., g_t)$.
 \emptyset (7)
 countered previously.

Iterative optimization involves performing the

llowing operations in each epoch (denoted as *t*):

(1) Calculate the gradient of the objective function with

spect to the current parameter using (5 (a) Number of epochs = 25 train loss
 $\begin{array}{|l|l|}\n\hline\n\text{train acc} \\
\hline\n\text{train loss} \\
\hline\n\text{val acc} \\
\hline\n\text{val loss}\n\end{array}$

(b) Number of epoch

(b) Number of epochs = 50

aining results for different numbers of epochs. Fig. 5. AlexNet training results for different numbers of epochs.

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The hyperparameters and loss function between the
sof the VGG16 classifier are presented in Table IV.
Ress, therefore, a LogSoftmax function was
ned to the output laver.
Tabl **IAENG International Journal of Computer Science**

The hyperparameters and loss function between the

layers of the VGG16 classifier are presented in Table IV.

Unlike AlexNet, the loss function of VGG16 was Table V.

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The hyperparameters and loss function between the
layers of the VGG16 classifier are presented in Table IV.
Unlike AlexNet, the loss function of VGG16 was
NLLLoss; therefore, a LogSoftmax functio IAENG International Journal

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ssifier are presented in Table IV.

loss function of VGG16 was

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TABLE IV

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Argument The hyperparameters and loss function between the

res of the VGG16 classifier are presented in Table IV.

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ike AlexNet, the loss function of VGG16 was

Table V.

LLoss; therefore, a LogSoftmax functio

Layer name	Argument	fc
fc1	nn.Linear(25088,4096)	Loss function n
relu1	nn. Relu()	The training results for Res
fc2	nn.Linear(4096,1000)	are shown in Fig. 7. The conv not as effective as that of the
relu2	$nn.$ Relu()	addition, the loss value of the
fc3	nn.Linear(1000,8)	under that of the training set,
output	nn.LogSoftmax(dim=1)	because of overfitting. Alt occurred because the loss va
Loss function	nn.NLLLoss()	training set were calculated du
	The training results for VGG16 at different epochs are shown in Fig. 6. When epoch=6, the loss value of the validation set surged slightly, continued to decline between epochs 6 and 13, and then stabilized. When epoch=15, the accuracy of the validation set reached the highest accuracy of 87.70%. Similarly, the loss value of the training set decreased significantly before epoch=10 and then it fluctuated between 0.31 and 0.32 and the	each epoch, whereas the loss validation set were calculated The loss value of the training until epoch=10, after which it range. Similarly, the accur fluctuated more slowly after terms of the general direction number of epochs were incre would not have been obtain

For the raining results for VGG16 at different epochs are some in the solution, the loss value of the raining set, we can be the solution, the loss value of the training set, we can be the solution of the training results relu2 mn.Relu()

addition, the loss value

fa3 mn.Linear(1000,8)

anddition, the loss value

to the training

occurred because of overfitting

loss function

Loss function

Loss function

loss function

to the training set For the training set fluctuated between 0.31 and 0.32, and the discussion and then it fluctuated between 0.86 and 1.087.

Youth the training set were calculated due and peak of overfitting. Although the training set were c accuracy of the training set fluctuated between 0.86 and the dataset all

because of overfitting. All

because of overfitting. All

cocurred because the loss

The training results for VGG16 at different epochs are

arining 0.87.

number of categories required by the system, which was eight. The modified content and loss function are listed in Table V.
Table V. **and of Computer Science**

number of categories required by the system, which was

eight. The modified content and loss function are listed in

Table V.

TABLE V

<u>SETTINGS USED FOR RESNET50 FOR SORTING</u>

epoch=15, the accuracy of 87.70%. Similarly, the loss value of the raining set decreased significantly before spock-10 accuracy of the raining set decreased in the set of the validation set reached the validation set with number of categories required by the system, which was

eight. The modified content and loss function are listed in

Table V.

SETINGS USED FOR RESNET50 FOR SORTING

Layer name

for m.Linear(2048,8)

Loss function m.CrossE eight. The modified content and loss function are listed in
Table V.
TABLE V
SETTINGS USED FOR RESNET50 FOR SORTING
Layer name Argument
for the mn.Linear(2048,8)
Loss function mn.CrossEntropyLoss()
The training results for Table V.

SETTINGS USED FOR RESNET50 FOR SORTING

Layer name

for an.Linear(2048,8)

Loss function m.CrossEntropyLoss()

The training results for ResNet50 at different epochs

are shown in Fig. 7. The convergence of ResNe TABLE V

SETTINGS USED FOR RESNET50 FOR SORTING

Layer name

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Loss function

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Loss function

The training results for ResNet50 at different epochs

are shown in Fig. 7. The convergence of ResNet50 was

not as eff SETTINGS USED FOR RESNET50 FOR SORTING

Layer name Argument

fc m.Linear(2048,8)

Loss function m.CrossEntropyLoss()

The training results for ResNet50 at different epochs

are shown in Fig. 7. The convergence of ResNet50 Layer name Argument

Layer name Argument

fc m.Linear(2048,8)

Loss function m.CrossEntropyLoss()

The training results for ResNet50 at different epochs

are shown in Fig. 7. The convergence of ResNet50 was

not as effecti Layer name Argument

for m.Linear(2048,8)

Loss function m.CrossEntropyLoss()

The training results for ResNet50 at different epochs

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Ios function mn.CrossEntropyLoss()

Loss function mn.CrossEntropyLoss()

The training results for ResNet50 at different epochs

are shown in Fig. 7. The convergence of ResNet50 was

not as effective as that of the prev Loss function

The training results for ResNet50 at different epochs

are shown in Fig. 7. The convergence of ResNet50 was

not as effective as that of the previous two models. In

addition, the loss value of the validati Loss innetion

IncrossmitopyLoss()

The training results for ResNet50 at different epochs

are shown in Fig. 7. The convergence of ResNet50 was

not as effective as that of the previous two models. In

addition, the loss v The training results for ResNet50 at different epochs
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not as effective as that of the previous two models. In
addition, the loss value of the validation set was always
u Ine training results for ResNet50 at different epochs
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anddition, the loss value of the previous two models. In
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addition, the loss value of the validation set was always
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trainin under that of the training set, which may have occurred
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training set were calculated during the training process of
ea because of overniting. Alternatively, it may have
occurred because the loss value and accuracy of the
training set were calculated during the training process of
evalidation set were calculated after each training epoch.
T occurred because the loss value and accuracy or
training set were calculated during the training process
each epoch, whereas the loss value and accuracy of
validation set were calculated after each training epo
The loss v

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exhibited accuracies higher than that of ResNet50, their
loss values were below 0.33, and their range of
fluctuations was relatively small and tended to converge.
In contrast IAENG International Journal of Computer Science
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loss values were below 0.33, and their range of
fluctuations was relatively small and tended to converge.
In contrast, exhibited accuracies higher than that of ResNet50, their
loss values were below 0.33, and their range of
fluctuations was relatively small and tended to converge.
In contrast, at the beginning of the training, the accuracy After training the three models, the same test set was the same test set was the same test set was all the same test set was three models was between 0.7 and 0.8, and as training proceeded, the accuracy gradually increased exhibited accuracies higher than that of ResNet50, their

loss values were below 0.33, and their range of

fluctuations was relatively small and tended to converge.

In contrast, at the beginning of the training, the accur exhibited accuracies nigher than that of Resivets. Their range of
fluctuations was relatively small and their range of
fluctuations was relatively small and the training, the accuracy
of the ResNet50 model was between 0.7 FREE VI

ACCULATED SIGNATES WAS PERICULATED SIGNATIONS WAS relatively small and tended to converge.

In contrast, at the beginning of the training, the accuracy

of the ResNet50 model was between 0.7 and 0.8, and as

the t THE TRIGHTERT THE TRIGHTERT THE TRIGHTERT ONDERT THE TRIGHTERT ONTARISON BETWEEN THE THREE MODELS (THE TRIGHTERT ONDERT THE THACK OF THE THACK ON THE TRIGHTERT ON THE TRIGHTERT ON THE TRIGHTERT ON THE TRIGHTERT ON THE TRIG

changer and Calician sets was relatively
and validation sets was relatively
of the validation set was always
raining set.
the same test set was
v one, with a total number of 701
i comparison between the highest
on set and The three models, the same test set was
them one by one, with a total number of 701
e VI shows a comparison between the highest
the validation set and the accuracy of the test
of the three models at epoch=50.
The
TABLE VI

samples

Test set

accuracy

89.02% 86.16% 85.73%

Externe contractors and DRESULTS

4. System testing

For system construction and testing, a rando

corn disease image was selected, the image and pa

displayed on the main

VI. SYSTEM TESTING AND RESULTS

A. System testing

for system construction and testing, a random local

For system construction and testing, a random local

corn disease image was selected, the image and path were

display VI. SYSTEM TESTING AND RESULTS
 A. System testing

For system construction and testing, a random local

corn disease image was selected, the image and path were

displayed on the main interface, one of the three models
 VI. SYSTEM TESTING AND RESULTS

A. System testing

For system construction and testing, a random local

corn disease image was selected, the image and path were

displayed on the main interface, one of the three models

wa VI. SYSTEM TESTING AND RESULTS

A. System testing

For system construction and testing, a random local

corn disease image was selected, the image and path were

displayed on the main interface, one of the three models

re A. System testing

For system construction and testing, a random local

corn disease image was selected, the image and path were

displayed on the main interface, one of the three models

was selected and used for recognit 1. Bystem testing

For system construction and testing, a random lo

corn disease image was selected, the image and path w

displayed on the main interface, one of the three mood

was selected and used for recognition, and

bottom, corn gray spot (severe), corn leaf spot (severe), corn gray spot (general), corn leaf spot (general), and bottom, corn gray spot (severe), corn leaf spot (severe), corn gray spot (severe), and corn rust (severe). Their corresponding corn leaf spot (severe), corn gray spot (severe), and corn rust (severe). Their corresponding c Experience of the corresponding to the same maize of the spot (general), spot (general), and spot (general), corn leaf spot (general), and corn rust (severe). Their corresponding probabilities were 0.95, 0.05, 0.005, 2.09e Examples the main of the same according to the severe of the severe Site of

Site of

Site of

Site of

Fig. 8. Image recognized by AlexNet.

The results of VGG16's recognized by AlexNet.

The results of VGG16's recognition of the same maize

disease image are shown in Fig. 10. As shown in

Volume 52, Issue 1, January 2025, Pages 111-120

IAENG International Journal of Computer Science
to bottom, corn gray spot (severe), corn gray spot
(general), corn leaf spot (severe), corn rust (severe), and
corn health. Their corresponding probabilities were
387.09, 234 IAENG International Journal of Computer Science
to bottom, corn gray spot (severe), corn gray spot
(general), corn leaf spot (severe), corn rust (severe), and
corn health. Their corresponding probabilities were
387.09, 234 **IAENG International Journal of Computer Science**
to bottom, corn gray spot (gevere), corn gray spot
(general), corn leaf spot (severe), corn rust (severe), and
corn health. Their corresponding probabilities were
387.09, IAENG International Journal of Comp
to bottom, corn gray spot (severe), corn gray spot
(general), corn leaf spot (severe), corn rust (severe), and
corn health. Their corresponding probabilities were
387.09, 234.22, 0.99, 0

COMPLARE THE CONDUCTED THE NEW THE NEW THE NEW THE NEW THE NEW THE NEW THOM THE NEW THE SERVED ON THE METHOD OF INTEREST AND MONETON CONDUCT THE NEW THE DISPONDING SURVEY OF THE DISPONDING DETERMINED AND NOTE THAT AND NOT produced by the matterial probability of identification with the database, and then the produced by the specification analysis

The function of identifying unidentified local pictures

is roughly as follows: select the loc Fig. 13. Prediction probabilities generated by ResNet50.

B. Verification probabilities generated by ResNet50.

B. Verification Analysis

The function of identifying unidentified local pictures

is roughly as follows: sel Select any heather and the processed inage is a shown in Fig. 13. Prediction probabilities generated by ResNet50.

The function of identifying unidentified local pictures

The function of identifying unidentified local pi Fig. 13. Prediction probabilities generated by ResNet50.

B. Verification Analysis

The function of identifying unidentified local pictures

is roughly as follows: select the local picture that needs to

be identified and Fig. 13. Prediction probabilities generated by ResNet50.

B. Verification Analysis

The function of identifying unidentified local pictures

is roughly as follows: select the local picture that needs to

be identified and *B. Verification Analysis*

The function of identifying unidentified local pictures

is roughly as follows: select the local picture that needs to

be identified and display it, extract the feature map of the

picture, id *B. Verification Analysis*

The function of identifying unidentified local pictures

is roughly as follows: select the local picture that needs to

be identified and display it, extract the feature map of the

picture, ide

15.

Fig. 15. RGB three channel information display of original image.

Select any of the three pre-trained models to identify it.

Take ResNet50 as an example. ResNet50 adopts a

Bottleneck structure, which mainly introduces Fig. 15. RGB three channel information display of original image.

Select any of the three pre-trained models to identify it.

Take ResNet50 as an example. ResNet50 adopts a

Bottleneck structure, which mainly introduces Fig. 15. RGB three channel information display of original image.
Select any of the three pre-trained models to identify it.
Take ResNet50 as an example. ResNet50 adopts a
Bottleneck structure, which mainly introduces $1\times$ Fig. 15. RGB three channel information display of original image.
Select any of the three pre-trained models to identify it.
Take ResNet50 as an example. ResNet50 adopts a
Bottleneck structure, which mainly introduces $1\times$ Fig. 15. RGB three channel information display of original image.

Select any of the three pre-trained models to identify it.

Take ResNet50 as an example. ResNet50 adopts a

Bottleneck structure, which mainly introduces Fig. 15. RGB three channel information display of original image.

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Take ResNet50 as an example. ResNet50 adopts a

Bottleneck structure, which mainly introduces Fig. 15. RGB three channel information display of original image.

Select any of the three pre-trained models to identify it.

Take ResNet50 as an example. ResNet50 adopts a

Bottleneck structure, which mainly introduces Fig. 15. RGB three channel information display of original image.

Select any of the three pre-trained models to identify it.

Take ResNet50 as an example. ResNet50 adopts a

Bottleneck structure, which mainly introduces Select any of the three pre-trained models to identify it.
Take ResNet50 as an example. ResNet50 adopts a
Bottleneck structure, which mainly introduces 1×1
convolution, that is, it can raise and reduce the number of
ch Select any of the three pre-trained models to identify it.
Take ResNet50 as an example. ResNet50 adopts a
Bottlencek structure, which mainly introduces 1×1
convolution, that is, it can raise and reduce the number of
ch Take ResNet50 as an example. ResNet50 adopts a
Bottleneck structure, which mainly introduces 1×1
convolution, that is, it can raise and reduce the number of
channels (cross-channel information integration), and
realize Bottleneck structure, which mainly introduces 1×1
convolution, that is, it can raise and reduce the number of
channels (cross-channel information integration), and
realizes linear combination of multiple feature graph convolution, that is, it can raise and reduce the number of
channels (cross-channel information integration), and
realizes linear combination of multiple feature graph
maintained.Compared with other convolution kernels, t channels (cross-channel information integration), and
realizes linear combination of multiple feature graph
pairs.
At the same time, the original feature map size is
maintained.Compared with other convolution kernels, the realizes innear combination of multiple reature graph
pairs. At the same time, the original feature map size is
maintained. Compared with other convolution kernels, the
computational complexity can be greatly reduced. If pairs. At the same time, the original reature map size is
maintained. Compared with other convolution kernels, the
computational complexity can be greatly reduced. If you
use two 3×3 convolution stacks, there is only one maintained. Compared win other convolution kernets, the
computational complexity can be greatly reduced. If you
use two 3×3 convolution stacks, there is only one ReLU
activation function, but with 1×1 convolution computational complexity can be greatly reduced.IT you
use two 3×3 convolution stacks, there is only one ReLU
activation function, but with 1×1 convolution you will
have two ReLU activation functions, introducing mo use two 3×3 convolution stacks, there is only one KeLU
activation function, but with 1×1 convolution you will
have two ReLU activation functions, introducing more
nonlinear mapping. The entire ResNet does not use
Dr

IAENG International Journal of Compute
and Softmax's 1000-way fully connected layer. The number of feature
For feature extraction of this image, the size of the first is 28×28. After the
layer of convolutional kernel of **IAENG International Journal of Computer Science**

d Softmax's 1000-way fully connected layer.

For feature extraction of this image, the size of the first is 28×28 . After the layer3 concer of convolutional kernel of **IAENG International Journal of Computer**
and Softmax's 1000-way fully connected layer. The number of features
For feature extraction of this image, the size of the first is 28×28 . After the
layer of convolutional ker **IAENG International Journal of Computer Science**
and Softmax's 1000-way fully connected layer. The number of features extracted if
or feature extraction of this image, the size of the first is 28×28 . After the layer3 **IAENG International Journal of Computer Science**

and Softmax's 1000-way fully connected layer. In umber of features extracted i

For feature extraction of this image, the size of the first

is 28×28. After the layer3 co **TAENG International Journal of Computer Science**

and Softmax's 1000-way fully connected layer. The number of features extracted

For feature extraction of this image, the size of the first

alger of convolutional kernel **IAENG International Journal of Computer Science**

and Softmax's 1000-way fully connected layer.

For feature extracted on this image, the size of the first

is 28×28. After the layer3 convolutional

layer of convolutiona **IAENG International Journal of Computer S**
and Softmax's 1000-way fully connected layer. The size of the first is 28×28. After the layer of convolutional kernel of ResNet50 convolutional number of extracted
neural networ **IAENG International Journal of Computer**

and Softmax's 1000-way fully connected layer.

For feature extraction of this image, the size of the first is 28×28. After the

layer of convolutional kernel of ResNet50 convolut **IAENG International Journal of Computer Science**

and Softmax's 1000-way fully connected layer.

For feature extraction of this image, the size of the first

is 28×28.After the layer3 convolutional kernel of ResNet50 con and Softmax's 1000-way fully connected layer.

For feature extracted For feature extracted of this image, the size of the first

is 28×28. After the layer3 collator of convolutional kernel of ResNet50 convolutional

numbe and Softmax's 1000-way fully connected layer.

For feature extraction of this image, the size of the first

layer of convolutional kernel of ResNet50 convolutional

neural network is 7×7, the operation step is 2, and the
 and Softmax's 1000-way fully connected layer.

For feature extraction of this image, the size of the first

layer of convolutional kernel of ResNet50 convolutional

neural network is 7×7, the operation step is 2, and the
 er of convolutional kernel of this layer 1
fore, after calculation, the number of feature
ted by using the first layer of convolutional la
et50 network is 64.The size of each is 112×11
alculation of the output size of The single, the size of the first is 28×28 . After the layer

of this image, the size of the first is 28×28 . After the layer

rmel of ResNet50 convolutional number of extracted feature

and kernel of this layer is ver of convolutional kernel of ResNet50 convolutional

umber of extracted features

ural network is 7×7, the operation step is 2, and the

mber of convolutional kernel of this layer is 64.

mumber of extracted features

t neural network is 7×7, the operation step is 2, and the 14×14.After the layer4 convolutional kernel of this layer is 64. Interfector, after calculation, the number of ecature maps $\frac{7 \times 7}{1}$.

Therefore, after calculat number of convolutional kernel of this layer is 64.

Therefore, after calculation, the number of feature maps

extracted fo that layer of convolutional layer of 7×7 .

ResNet50 network is 64. The size of each is 112×112 Therefore, after calculation, the number of feature maps

extracted by using the first layer of convolutional layer of

ResNet50 network is 64.The size of each is 112×112.For

the calculation of the output size of the con

extracted by using the first layer of convolutional layer of

ResNet50 network is 64.The size of each is 112×112 .For

the calculation of the output size of the convolutional

layer, as shown in Fig. 1

equation (10), w ResNet50 network is 64.The size of each is 112×112 .For
the calculation of the output size of each is 112×112 .For
the calculation of the output size of the convolutional
layer, as shown in Fig. 18.
layer, the specifi the calculation of the output size of the convolutional
layer, as shown in Fig. 18.
layer, the specific calculation formula is shown in
equation (10), where input represents the input size,
kemel represents the convolutio layer, the specific calculation formula is shown in
equation (10), where input represents the input size,
exemel represents the convolution kernel size, and stride
represents the step size.
 $\frac{\text{stride}}{\text{stride}}$
 $\frac{\text{crip}}{\text{tride$ equation (10), where input represents the input size,

kernel represents the convolution kernel size, and stride

represents the step size.
 $output = \frac{input + 2x_{spaddle-kernel}}{stride} + 1$ (10)

Fig. 16 shows the feature map extracted from th kernel represents the convolution kernel size, and stride
represents the step size.
 $output = \frac{input+2xpadding-kernel}{stride} + 1$ (10)
Fig. 16 shows the feature map extracted from the first
convolution layer of ResNet50, which shows that the
d represents the step size.

output = $\frac{input+2xpadding-kernel}{stride}+1$ (10)

Fig. 16 shows the feature map extracted from the first

convolution layer of ResNet50, which shows that the

edge features of the image are mainly extracted t output = $\frac{input + 2xpadding-kernel}{stricted from the first}$ (10)

Fig. 16 shows the feature map extracted from the first

convolution layer of ResNet50, which shows that the

edge features of the image are mainly extracted through

the first convolu Fig. 16 shows the feature map extracted from the first
convolution layer of ResNet50, which shows that the
edge features of the image are mainly extracted through
the first convolution layer. At the same time, this 112×112

number of features extracted is 512, and the size of each
is 28×28 . After the layer3 convolution is completed, the
number of extracted features is 1024, each with a size of
 14×14 . After the layer4 convolution is c **is 28×28.After the layer3** convolution is completed, the number of eatures extracted is 512, and the size of each is 28×28.After the layer3 convolution is completed, the number of extracted features is 1024, each with a number of features extracted is 512, and the size of each
is 28×28 . After the layer3 convolution is completed, the
number of extracted features is 1024, each with a size of
 14×14 . After the layer4 convolution is com 14×14.After the layer4 convolution is completed, the **number of features extracted is 512, and the size of each is 28×28. After the layer3 convolution is completed, the number of extracted features is 1024, each with a size of** 14×14 **. After the layer4 convolution is compl** 7×7. I of Computer Science

mber of features extracted is 512, and the size of each

28×28.After the layer3 convolution is completed, the

mber of extracted features is 1024, each with a size of

×14.After the layer4 convolutio **and of Computer Science**
number of features extracted is 512, and the size of each
is 28×28 . After the layer3 convolution is completed, the
number of extracted features is 1024, each with a size of
14×14. After the l **and of Computer Science**

number of features extracted is 512, and the size of each

is 28×28.After the layer3 convolution is completed, the

number of extracted features is 1024, each with a size of

14×14.After the laye

Fig. 18. Feature extraction of convolutional layer via ResNet50.
The system developed in this study used images of corn
diseases to train the relevant network model, and then
obtained the images by reading the local image Fig. 18. Feature extraction of convolutional layer via ResNet50.
The system developed in this study used images of corn
diseases to train the relevant network model, and then
obtained the images by reading the local image Fig. 18. Feature extraction of convolutional layer via ResNet50.
The system developed in this study used images of corn
diseases to train the relevant network model, and then
obtained the images by reading the local image Fig. 18. Feature extraction of convolutional layer via ResNet50.
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diseases to train the relevant network model, and then
obtained the images by reading the local image Fig. 18. Feature extraction of convolutional layer via ResNet50.
The system developed in this study used images of corn
diseases to train the relevant network model, and then
obtained the images by reading the local image Fig. 18. Feature extraction of convolutional layer via ResNet50.
The system developed in this study used images of corn
seases to train the relevant network model, and then
tained the images by reading the local image set, Fig. 18. Feature extraction of convolutional layer via ResNet50.
The system developed in this study used images of corn
diseases to train the relevant network model, and then
obtained the images by reading the local image Fig. 18. Feature extraction of convolutional layer via ResNet50.
The system developed in this study used images of corn
diseases to train the relevant network model, and then
obtained the images by reading the local image The system developed in this study used images of corn
diseases to train the relevant network model, and then
obtained the images by reading the local image set,
identified the corn leaves using the deep learning model,
co The system developed in this study used images of corn
diseases to train the relevant network model, and then
obtained the images by reading the local image set,
identified the corn leaves using the deep learning model,
co diseases to train the relevant network model, and then
obtained the images by reading the local image set,
identified the corn leaves using the deep learning model,
compared the description of the disease characteristics,

obtained the images by reading the love
identified the corn leaves using the deep l
compared the description of the disease
and evaluated the types of diseases and pes
healthy corn leaves, corn gray spots (sev
spots (sever entified the corn leaves using the deep learning model,
mpared the description of the disease characteristics,
d evaluated the types of diseases and pests, which were
althy corn leaves, corn gray spots (severe), corn leaf
 compared the description of the disease characteristics,
and evaluated the types of diseases and pests, which were
healthy corn leaves, corn gray spots (severe), corn leaf
spots (severe), and corn rust (general).
Tradition and evaluated the types of diseases and pests, which were
healthy corn leaves, corn gray spots (severe), corn leaf
spots (severe), and corn rust (general).
Traditional disease identification methods rely on
human experienc

healthy corn leaves, corn gray spots (severe), corn leaf
spots (severe), and corn rust (general).
Traditional disease identification methods rely on
human experience to identify diseases, but this method
results in relativ spots (severe), and corn rust (general).

Traditional disease identification methods rely on

human experience to identify diseases, but this method

results in relatively large errors and requires highly

skilled personne Traditional disease identification methods rely on
human experience to identify diseases, but this method
results in relatively large errors and requires highly
skilled personnel. In this study, a CNN model based on
deep l human experience to identify diseases, but this method
results in relatively large errors and requires highly
skilled personnel. In this study, a CNN model based on
deep learning was proposed to identify maize pests and
di results in relatively large errors and requires highly skilled personnel. In this study, a CNN model based on deep learning was proposed to identify maize pests and diseases, and different network models were compared via skilled personnel. In this study, a CNN model based on
deep learning was proposed to identify maize pests and
diseases, and different network models were compared
via experiments.
To distinguish between different diseases France in the model of the compared
etween different diseases and pests on
crop, which is difficult and thus not
rch progress, this study established a
fication system. The system can detect
ving the relevant features in u In distinguish between different diseases and pests on

2 same type of crop, which is difficult and thus not

nducive to research progress, this study established a

2 m disease database and designed and implemented a

2 o To distinguish between different diseases and pests on
the same type of crop, which is difficult and thus not
conducive to research progress, this study established a
corn disease database and designed and implemented a
er the same type of crop, which is difficult and thus not conducive to research progress, this study established a corn disease database and designed and implemented a crop disease identification system. The system can detect

IAENG International Journal of Computer Scie
Three common CNN models were selected: AlexNet,
VGG16, and ResNet50. These models were pre-trained
using processed datasets, and the loss values and
accuracies were calculated **IAENG International Journal of Computer Sc**
Three common CNN models were selected: AlexNet,
VGG16, and ResNet50. These models were pre-trained
using processed datasets, and the loss values and
accuracies were calculated f **IAENG International Journal of Computer Science**

Three common CNN models were selected: AlexNet,

VGG16, and ResNet50. These models were pre-trained

using processed datasets, and the loss values and

accuracies were cal **IAENG International Journal of Computer Science**

Three common CNN models were selected: AlexNet,

VGG16, and ResNet50. These models were pre-trained

using processed datasets, and the loss values and

accuracies were ca **IAENG International Journal of Computer Scien**

Three common CNN models were selected: AlexNet,

VGG16, and ResNet50. These models were pre-trained

using processed datasets, and the loss values and

accuracies were calcu **IAENG International Journal of Computer Science**

Three common CNN models were selected: AlexNet,

VGG16, and ResNet50. These models were pre-trained

using processed datasets, and the loss values and

accuracies were ca **IAENG International Journal of Computer Science**

Three common CNN models were selected: AlexNet,

WGG16, and ResNet50. These models were per-trained

using processed datasets, and the loss values and

accuracies were ca **IAENG International Journal of Computer Science**

Three common CNN models were selected: AlexNet,

VGG16, and ResNet50. These models were pe-trained

using processed datasets, and the loss values and

accuracies were calc **IAENG International Journal of Computer Science**

Three common CNN models were selected: AlexNet,

VGG16, and ResNet50. These models were pre-trained

using processed datasets, and the loss values and

accuracies were ca follows. Three common CNN models were selected: AlexNet,

VGG16, and ResNet50. These models were pre-trained

using processed datasets, and the loss values and

accuracions of the Chinese Society

training and validation processes Three common CNN models were selected: AlexNet,

WGG16, and ResNet50. These models were pre-trained

using processed datasets, and the loss values and

accuracies were calculated for each model during the

training and va Three common CNN models were selected: AlexNet,

VGG16, and ResNet50. These models were pre-trained

using processed datasets, and the loss values and

training and validation processes. The pre-trained model during the
 VGG16, and ResNet50. These models were pre-trained

using processed datasets, and the loss values and

accuracies were calculated for each model during the

training and validation processes. The pre-trained models

train using processed datasets, and the loss valuated accuracies were calculated for each model duratining and validation processes. The pre-trained were compared to the three network models; for the dataset, AlexNet and VGG16 e accuracies were calculated for each model during the *Emissacions of the Chinese Society*

training and validation processes. The pre-trained models

(2) S. P. Jia, H. J. Gao, and X. His

were compared to the three networ training and validation processes. The pre-trained models [2] S. P. Jia, H. J. Gao, and

were compared to the three network models; for the same

learning," Transactions

dataset, AlexNet and VGG16 exhibited fewer

learni

were compared to the three network models; for the same

learning," Transactions of the

dataset, AlexNet and VGG16 exhibited fewer

primary contributions when converging than did ResNet50. The

primary contributions of t dataset, AlexNet and VGG16 exhibited fewer

Huctuations when converging than did ResNet50. The

primary contributions of this study can be summarized as

follows.

(1) Maize disease images were collected for the system

u fluctuations when converging than did ResNet50. The [3] W. Peng, Y. B. Lan, and X. J

primary contributions of this study can be summarized as

follows.

(1) Maize disease images were collected for the system

(1) Maize d primary contributions of this study can be summarized as

follows.

(1) Maize disease images were collected for the system

(4) Y. H. Zhang, J. S. Wang,

(1) Maize disease images were collected for the system

were divide Follows.

(1) Maize disease images were collected for the system

using a web crawler and other methods, and these images

network," Engineering Letter

income divided into training, verification, and test sets at a algor (1) Maize disease images were collected for the system

using a web crawler and other methods, and these images

were divided into training, verification, and test sets at a

ratio of 6.2:2. The images were standardized t using a web crawler and other methods, and these images

were divided into training, verification, and test sets at a

algorithms based on deep learning

214 × 224 pixels. The images were standardized to a size of

224 × were divided into training, verification, and test sets at a

ratio of 6:2:2. The images were standardized to a size of

224×224 pixels.

(2) A CNN model was adopted for deep learning, and

three common CNN models were se (3) The system is a size of the system retained by the system recommon CNN models were selected: AlexNet,

3, pp. 560-568, 2024.

The system recommon CNN models were selected: AlexNet,

Systems (CSCDS), pp. 462-

3. The s 224×224 pixels.

(2) A CNN model was adopted for deep learning, and

the common CNN models were selected: AlexNet,

WGGI6, and ResNet50. The model was pre-trained using

the processor, "*Excremics*, we

displayed the proc (2) A CNN model was adopted for deep learning, and

three common CNN models were selected: AlexNet,

VGG16, and ResNet50. The model was pre-trained using

VGG16, and ResNet50. The model was pre-trained using

the processo three common CNN models were selected: AlexNet,

VGG16, and ResNet50. The model was pre-trained using

the processed dataset mentioned above. The loss value

and scrue and scrue and accuracy of each model during training

VGG16, and ResNet50. The model was pre-trained using
the processed dataset mentioned above. The loss value
the processor, "*Electronics*, vol.
and accuracy of each model during training and
and images is and s. K. S. "App the processed dataset mentioned above. The loss value

and accuracy of each model during training and

verification were calculated, and the pre-trained model

and S. K. S. "Applications of

werification were calculated, and accuracy of each model during training and

verification were calculated, and the pre-trained model

was saved. Next, we compared the three network models

was saved. Next, we compared the three network models

also s verification were calculated, and the pre-trained model

was saved. Next, we compared the three network models

and found that, for the same dataset, the fluctuation
 $\begin{bmatrix}\n0\end{bmatrix}$ L. Neyligi, M. Abelwhaha, and

and fo was saved. Next, we compared the three network mod
and found that, for the same dataset, the fluctuati
amplitudes of AlexNet and VGG16 were smaller th
that of ResNet50 in the convergence process.
(3) The system recognized (4) found that, for the same dataset, the fluctuation
 $\frac{1}{2}$ L. Negative, New and Handel and NGG16 were smaller than
 $\frac{1}{2}$ in mage processing techniques

and of ResNet50 in the convergence process.
 $\frac{1}{2}$ The amplitudes of AlexNet and VGG16 were smaller than

that of ResNet50 in the convergence process.

(3) The system recognized unmarked maize disease

(5) G. Debasis and B. Mean, "Pest identify the results using a query datab that of ResNet50 in the convergence process.

(3) The system recognized unmarked maize disease

in crop fields through images and displayed the results using a query database.

In the process of recognizing unrecognized m (3) The system recognized unmarked maize disease

in crop fields through

images and displayed the results using a query database.

In the process of recognizing unrecognized maize disease

in crop fields through

images,

images and displayed the results using a query database.

In the process of recognizing unrecognized maize disease

images, the original image was first processed, and then

identure actuation was performed on the image t In the process of recognizing unrecognized maize disease inals, pp. 28-2-294,

images, the original image was first processed, and then

feature extraction was performed on the image through

the network. At the end of th images, the original image was first processed, and then

feature extraction was performed on the image through

the network. At the end of the recognition, five disease

outcomes with high probabilities were predicted, a feature extraction was performed on the image through

the network. At the end of the recognition, five disease

outcomes with high probabilities were predicted, and the

one with the highest probability was designated as the network. At the end of the recognition, five disease $[22]$ E , E_{14} E , Q , E , and Y. B. Nutcomes with higher brobabilities were predicted, and the citres diseases and persis based on interval and the funder outcomes with high probabilities were predicted,
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trained using the dataset. These networks offer the detection based (4) The AlexNet, VGG16, and ResNet50 models were

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of Ale accuracy, and easy operation. Comparative experiments

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86.98%, 87.70%, and 85.98%, respectively. These results

demonstrate that the recognition accuracy of the pro of AlexNet, VGG16, and ResNet50 were approximately

86.98%, 87.70%, and 85.98%, respectively. These results
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demonstrate that the recognition accuracy of the proposed
 86.98%, 87.70%, and 85.98%, respectively. These result demonstrate that the recognition accuracy of the propose method was significantly higher than that of traditional method.
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The system recognizes the unmarked maize disease

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