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# Recognition of Locust Species Based on CNN

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**ABSTRACT:** The most significant field crops' growth is hampered by pest attacks, and agricultural productivity is decreased by numerous bug species. Pests of agriculture, locusts are widespread across the world. Because all locust kinds have a similar look, precisely classifying and identifying them can be challenging. Convolution neural network (CNN) with deep architectures is being used in image classification applications to do automatic feature extraction and train sophisticated high-level features in order to solve this problem. This work proposes a locust species recognition method based on ResNet101. The proposed method used ResNet101 as a feature extraction network, Transfer learning was applied to fine-tune the pre-trained model and data augmentation techniques are also applied to prevent the network from overfitting. Experiment performed to evaluate the accuracy of the proposed ResNet101 model show that the model can effectively classify different locust species.

## I.INTRODUCTION

Through history, people have venerated and dreaded locust infestations, which are frequently seen as natural catastrophes. A severe danger to agricultural output, locust outbreaks have the ability to do extensive harm. Locust swarms are still active today and may be seen in many regions of the world. The livelihoods of people involved in crop production and those who depend on it for food and survival have been impacted by this calamity. The Acrididae family of short-horned grasshoppers known as locusts is often absolutely benign, but under specific weather patterns, they can be dangerous. Serotonin release is elevated in grasshoppers during periods of heavy and erratic rain, which eventually results in the transformation of grasshoppers into locusts. When locusts go from being solitary to becoming gregarious, they become dangerous. The solitary insects display gregarious traits and create swarms that wreak havoc on crops. They also generate morphological and behavioural changes in response to vegetation. Due to their complicated structure and a high degree of visual resemblance across different species, classifying locusts is a challenging process. Early identification and classification of locusts in crops is essential, particularly to stop their spread and the consequent application of efficient insecticides and biological control techniques. Therefore, identifying the locusts and keeping an eye on the insects can help avoid or postpone any potential swarm formation. The methods used to identify locusts today involve physically looking over sensitive areas and putting the data into a computer interface. The tracking of locusts also takes use of meteorological and soil data obtained by satellites. These methods have been useful in helping to identify locust activity early on. However, manual inspections could be a laborious and time-consuming process. This paper provides a deep learning-based method for classifying various locust species.

### 1.1 DEEP LEARNING

Artificial neural networks, which are algorithms inspired by the human brain, learn from vast amounts of data in deep learning, a type of machine learning. Even with a highly varied, unstructured, and linked data collection, deep learning enables machines to tackle complicated issues. As a powerful class of models for image classification in a number of issues in the agricultural area, such as plant disease detection, fruit classification, weed identification, and crop pest classification, deep learning models based on CNN have seen a lot of application recently. Multiple processing layers in deep learning models are used to learn representations of raw input at various degrees of abstraction.

Modern deep learning models have demonstrated outstanding accuracy in speech and object recognition, and they have been useful in other areas including medication design and genomics.

## **1.2 CONVOLUTIONAL NEURAL NETWORK**

Convolutional neural networks (CNN), which are used for processing and evaluating pictures or visual data, play a vital role in deep learning. An output layer, fully connected layers, blocks of convolutional and pooling layers, and fully connected layers make up the layers of a convolutional neural network, which has several layers. Using filters, the convolutional layer pulls the features from a picture. The outputs from the convolutional layer are further sub-sampled by the pooling layer, which also minimises the number of parameters. On the basis of inputs from lower levels, the completely linked layer operates in the current layer's neurons and produces output. Many CNN models have been created over the years, and each one has greater efficiency and a better, broader architecture. Popular neural network architecture AlexNet The VGGNet is another significant design. The number of parameters is decreased since it employs tiny size filters. ResNet, GoogleNet, and MobileNet are all significant architectures.

### **1.3 ResNet**

A more direct link for information to spread across the network is created by deep residual network, also known as ResNet, which performs well with very deep designs. Deep networks experience degradation issues as a result of an increase in network layers, when accuracy begins to saturate and quickly declines. The vanishing gradient issue that arises as network depth increases was addressed by ResNet. The vanishing gradient issue is not seen during back propagation with ResNet. Shortcut connections, also known as skip connections, are parallel to the regular convolutional layers of a residual neural network and aid in the network's understanding of global characteristics. There are several resnet variations, including ResNet18, ResNet50, and ResNet101. The layer architectures of ResNet18 and ResNet50 are different. ResNet50 has a bottleneck building block structure with an extra layer of 1 x 1 convolution, whereas ResNet18 just includes basic building blocks as layers. This allows ResNet50 to decrease and restore the dimensions.

#### **1.3.1 ResNet101**

ResNet-101 model, which has 101 recurrent connections between parametrized layers, A new fully connected layer comes before the softmax output layer in the ResNet-101. It has a 77-convolution layer with 64 kernels, a 33 max pooling layer with stride 2, 33 residual building blocks, a 77 average pooling layer with stride 7, and a new fully connected layer. The number of locust classes is indicated by setting the softmax output layer to n.

## **II.LITERATURE REVIEW**

### **2.1 Deep Residual Learning for Image Recognition**

For image categorization, deep convolutional neural networks have produced a number of achievements. The "levels" of features may be enhanced by the number of stacked layers (depth) in deep networks, which naturally incorporate low/mid/high level features and classifiers in an end-to-end multilayer way. Recent research demonstrates the critical relevance of network depth, and the top results on the difficult ImageNet dataset all use "very deep" models, with a depth of sixteen to thirty. When deeper networks may begin converge, a degradation issue is revealed: as network depth increases, accuracy becomes saturated and then rapidly declines. Unexpectedly, adding more layers to a sufficiently deep model increases training error, indicating that such deterioration is not the result of overfitting.

The decline in training accuracy shows that not every system is equally simple to optimise. comparing a deeper architecture with its shallower equivalent that has more layers. The deeper model may be solved by construction: identity mapping is used for the newly added layers, and the learnt shallower model is used for the other layers. A deeper model shouldn't create a bigger training error than its shallower version, according to the presence of this designed answer.

Training increasingly complex neural networks is more challenging. In order to make it easier to train networks that are far deeper than those previously employed, this research presents a residual learning approach. Instead of learning unreferenced functions, the layers in this study explicitly reformulate the layers to learn residual functions with reference to the layer inputs. It offers in-depth empirical proof that these residual networks are simpler to optimise and can improve accuracy over far more depth.

## **2.2 Very deep convolution network for large scale image recognition.**

ConvNets are becoming more commonplace in the field of computer vision, therefore many attempts have been made to enhance the original design in an effort to increase accuracy. For instance, lower receptive window sizes and shorter first convolutional layer strides were used in the best-performing submissions to the ILSVRC-2013. Another area of development focused on intensively training and testing the networks throughout the entire picture at numerous scales. This study discusses the depth of the ConvNet architectural design, another crucial component. Because all levels employ relatively tiny (3 3) convolution filters, it is possible to continuously increase the depth of the network by adding more convolutional layers. This fixes other architectural factors.

As a result, this paper developed significantly more accurate ConvNet architectures that can be used to perform state-of-the-art classification and localization tasks on the ILSVRC dataset as well as other image recognition tasks, where they perform well even when incorporated into straightforward pipelines.

This study examines how the convolutional network's depth affects its accuracy in the context of large-scale picture recognition. The key contribution is a detailed analysis of networks with increasing depth utilizing an architecture with extremely tiny (33) convolution filters, which demonstrates that extending the depth to 16–19 weight layers may significantly outperform existing designs. These results served as the foundation for our entry to the 2014 ImageNet Challenge, which helped our team win first and second place in the localization and classification tracks, respectively. Additionally, it demonstrates how effectively the representations generalize to different datasets, where they produce cutting-edge outcomes.

## **2.3 Training Object Detection and Recognition CNN Models Using Data Augmentation.**

One of the most crucial areas of computer vision is object detection and recognition since it is a necessary step for many applications, including smart homes, smart offices, surveillance, and robots. In this work, the authors concentrate on two distinct scenarios: finding commercial logos in the outdoors and finding items photographed in high quality (such as toys). The work of logo detection is crucial for online brand management, product placement verification, and contextual ad placement (the placement of pertinent adverts on websites, photos, and videos). Applications for learning or entertainment can make advantage of object detection to enhance user involvement.

Convolutional Neural Networks (CNN) may be used to perform essential tasks in object identification and recognition, including as feature extraction, region proposals, and classification, with high accuracy, according to recent advancements in deep learning techniques. However, there are substantial technical issues that need to be resolved when using CNNs for object detection and recognition. The extremely huge number of training pictures needed for each class or label is one of the most difficult issues. Data augmentation techniques, which apply linear and nonlinear changes to the training data to produce "new" training pictures, are one approach to solving this issue. Spatial flipping, warping, and other deformations are examples of typical transformations. Spatial flipping, warping, and other deformations are examples of typical transformations. The fact that the deformations applied to the training pictures with labels on them do not alter the semantic meaning of the classes or labels is a key idea in data augmentation. In this study, we explore various methods for data augmentation. First, the training dataset is expanded using a variety of data augmentation strategies. Then, a Faster R-CNN is trained to identify and recognise objects using the expanded dataset. Our research focuses on two distinct scenarios: finding items in the natural world (such as company logos) and finding objects that have been photographed using a camera installed on a computer system.

## **2.4 Identification of butterfly based on their shapes when viewed from different angles using an artificial neural network.**

The key to knowing ecology is often stressed as being accurate species identification. The identification procedure is essential for investigating evolutionary and developmental theories, for tracking the spread of pollutants and disease vectors, and for locating biodiversity hotspots. The identification method also has some significant practical uses in border security and agriculture, where invaders and pests must be located and eliminated before they establish themselves as unauthorised occupants of agricultural regions. Despite its significance, species identification is still a challenging, costly, and time-consuming procedure. This is due in part to the complexity of species shapes as well as a lack of knowledge regarding the important descriptors for many species.

Because they are intimately linked to crop plants used for human and animal nutrition, butterfly species identification is crucial. However, because of the intricate forms of butterflies, the commonly accepted trustworthy procedures for



butterfly identification are ineffective. In the past, we created a brand-new approach for recognising shapes that makes use of branch length similarity (BLS) entropy, a straightforward branching network with just one node and branches. The technique has been used to identify combat tanks and categorise human faces with various emotions. In the present study, it used the BLS entropy profile (an assemble of BLS entropies) as an input feature in a feed-forward back-propagation artificial neural network to identify butterfly species according to their shapes when viewed from different angles (for vertically adjustable angle,  $\theta = \pm 10^\circ, \pm 20^\circ, \pm 60^\circ$  and for horizontally adjustable angle,  $\phi = \pm 10^\circ, \pm 20^\circ, \dots, \pm 60^\circ$ ). Due to butterfly alignment and viewer orientation in the field, which produce different forms for a particular specimen, butterfly photographs are typically taken obliquely by camera. To generate different shapes of a butterfly when viewed from different angles, we projected the shapes captured from top-view to a plane rotated through angles  $\theta$  and  $\phi$ . The neural network was trained using projected forms with varying and values, then tested using different shapes. According to experimental findings, the approach was successful in differentiating different butterfly forms. This study also briefly discusses the development of the approach to recognise more intricate photos of other butterfly species.

### 2.5 An Insect Imaging System to Automate Rice Light-Trap Pest Identification.

In China, integrated pest management (IPM), which is based on monitoring and predicting paddy pests in conjunction with other many technical techniques including agricultural, biological, physical, and chemical treatments, is constantly used to control rice pests. Identification and counting of rice pests are crucial for tracking the dynamics of the pest population. In order to track the dynamics of the rice pest population, black light lamps are now often utilised to catch insects in paddy fields. The following day, these captured insects are brought in. Only rice pests are detected and tallied by plant protection technicians, while non-damaging insects are eliminated.

To track rice pest population dynamics and create pest forecasts, it's crucial to identify and count the bugs caught in light-traps on rice. The manual identification and counting of rice light-trap pests takes a lot of time, which causes tiredness and increases the mistake rate. To automate rice pest detection, a rice light-trap insect imaging system is created. To gather more picture characteristics, this system can take top and bottom photographs of each insect using two cameras. A technique is suggested for eliminating the background using the colour contrast between two photos of pests and non-pests. A support vector machine (SVM) classifier with a radial basis kernel function is built using 156 characteristics, including colour, shape, and texture properties of each bug. The seven-fold cross-validation is used to improve the accurate rate of pest identification.

## III. PROPOSED METHODOLOGY

### 3.1. INTRODUCTION

Based on ResNet101, a technique for recognising the species of locust is suggested. The dataset was first created by gathering photos of 14 distinct species of locust, scaling them to 224 pixels, then adding data to them. ResNet101, which comprises of convolutional layers, max pooling layers, one fully connected layer, and an output layer with a Softmax classifier, is employed in the proposed technique as the feature extraction network. The pre-trained model was adjusted using transfer learning. The model is put to the test by making predictions about the various species of locust, and the accuracy of tasks involving locust recognition is assessed. The suggested system's dataflow diagram is shown in Figure 1.

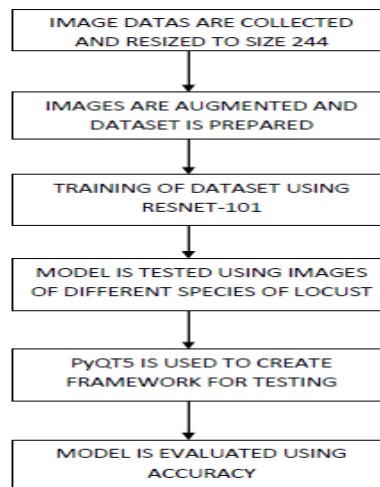


Figure 1: Dataflow diagram of proposed system

### 3.2. DATASET COLLECTION

To create the training and testing datasets, the picture datasets were manually gathered from web sources and pre-processed. There were 1533 total photos gathered, of which 1255 were used as the training set and 278 as the validation dataset.

No. of classes	Locust species
1	Aiolopus thalassinus
2	Calliptamus italicus
3	Chimarocephala pacifica
4	Chondracris rosea
5	Dactylotum Bicolor charpentier
6	Melanoplus Femurrubrum
7	Nomadacris septemfasciata
8	Omocestus viridulus
9	Phaulacridium marginale
10	Schistocerca Americana
11	Schistocerca gregaria
12	Valanga nigricornis
13	Caryanda Spuria
14	Valanga irregularis

Table 1: Locust species sample

Dataset preparation started with gathering photos of 14 distinct species of locust, scaling them to 224, and adding data which are shown in Table 1.

### 3.3 MODEL TRAINING

In this study, we assess ResNet-101, a residual network, for the categorization of locusts. ResNet-101 model, which employs transfer learning and has 101 parametrized layers with recurrent connections. A new fully connected layer comes before the softmax output layer in the ResNet-101. It has a 77 convolution layer with 64 kernels, a 33 max

pooling layer with stride 2, 33 residual building blocks, a 77 average pooling layer with stride 7, and a new fully connected layer. The number of locust classes in the dataset is indicated by the softmax output layer, which is set to 14. The model is put to the test by making predictions about the various species of locust, and the accuracy of tasks involving locust recognition is assessed. Stochastic gradient descent (SGD) is employed as the optimizer, while categorical cross entropy is used as the loss function.

### 3.4 MODEL TESTING

By predicting the various species of locusts, the trained model is put to the test. A framework is developed using PyQt5 designer for this testing in order to identify the different species of locust.

#### PyQT5

It is a Python plug-in implementation of the Qt cross-platform GUI toolkit. Free software known as PyQt was created by Riverbank Computing, a British company. On all supported platforms, including iOS and Android, Python may be used as an alternative to C++ for application development. It is implemented as more than 35 extension modules.

### 3.5 ARCHITECTURE OF RESNET-101

#### CONVOLUTION LAYERS:

The first layer, called the convolution layer, serves as a filter for feature extraction from the input data. 64 kernels make up the 77-convolution layer of the ResNet-101.

#### MAX POOLING LAYER:

The largest value from the area of the feature map that the filter has covered is chosen by max pooling layers. A feature map with the most noticeable features from the prior feature map is the result of the max pooling layer. With stride 2, the ResNet101 has a 33 maximum pooling layer.

#### RESIDUAL BLOCKS:

The remaining blocks carry out skip connections that omit two or more network levels. There are 33 residual blocks in the ResNet101.

#### AVERAGE POOLING LAYER:

Computes the average values for each patch of the supplied feature map after down sampling it. A stride 7 average pooling layer measuring 7 by 7.

#### FULLY CONNECTED LAYER:

It is a feed forward neural network. These layers, where each activation unit on one layer is coupled to every input on the one above it. The Softmax classifier receives the classification results as input. The number of classes is indicated by the softmax output layer, which is set to 14.

A pre-processing phase is carried out before to feeding the photos into the suggested structure. The first step is to reduce the original picture from 512 x 512 x 1 pixels to 128 x 128 x 1 pixels in order to reduce dimensionality, simplify computations, and enable the network perform better in less time. To keep the system trained on unsorted data and prevent concentrating on a certain area of the whole dataset, data are then separated and then shuffled. Three pieces of data—training, validation, and test sets—each with a separate goal label are used to organise the data (68% for training and 32% for system test and validation).

### 3.6 PROPOSED MODEL PARAMETERS

The suggested CNN model is trained with a learning rate of 0.01, 0.9 momentum, and SGD as the optimizer. The learning rate establishes the suggested model's learning trajectory and modifies the weight parameters to lower the network's loss function. In this experiment, a mini-batch size of 32 and a maximum of 10 epochs are both employed. A mini-batch is a portion of the training insect dataset used for testing the gradient descent loss function and updating the

weights. An epoch is the whole training cycle across the entire training locust dataset. The locust training dataset is used to train the model, and a validation frequency of 30 is used to measure accuracy on the testing dataset at regular intervals. Classification accuracy is an important evaluation metric used in our model and it is given by,

$$\text{Accuracy} = \frac{\text{Number of locusts predict correctly}}{\text{Total number of input locust samples}}$$

Categorical cross entropy is used as the loss function, which have softmax activations in the output.

### 3.7. ACCURACY AND LOSS CURVE

Figure 2,3 and 4 are the obtained performance metric and the obtained output.

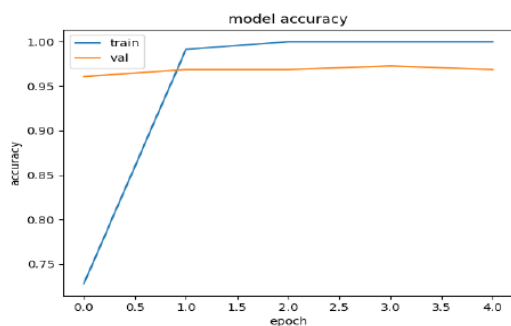


Figure 2: Accuracy curve

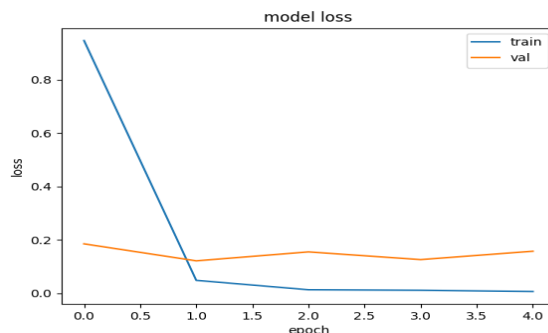


Figure 3: Loss curve

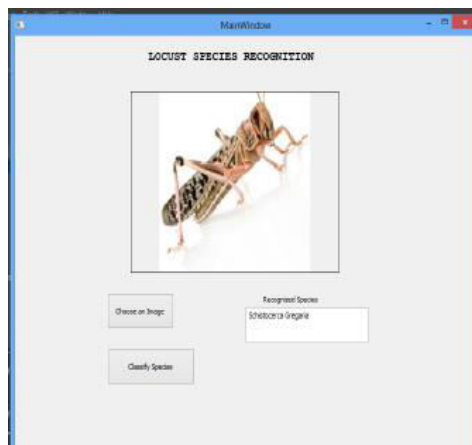


Figure 4: Output Screenshots of Locust Recognition

### IV.CONCLUSION

Field crop quality and yield are impacted by insect assaults. This research focused on the creation of pre-trained locust recognition algorithms and presented a CNN model. For our locust recognition task, a pre-trained model like ResNet-101 is used using a transfer learning strategy. In this paper, the impact of hyperparameters is also examined. The experimental findings demonstrate that our suggested CNN model, which has a sound architecture, can distinguish between various field crop insects with more accuracy than pre-trained models. The suggested CNN model for the locust dataset was able to achieve a classification accuracy of 96. Future work on the examined CNN model will concentrate on adding more locust classes, classifying insect subclasses, and speeding up computation. Additionally, the suggested study will be more beneficial to farmers for the early detection and categorization of locust in field crops



as well as for making quick judgements regarding the application of large amounts of pesticides in the afflicted crops in order to enhance the quality of the harvests.

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