RICE INSECTS CLASSIFICATION USIING TRANSFER LEARNING AND CNN

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Abstract-- **One of the biggest challenges to food security worldwide is insect pest attacks. Entomology has had many applications in many biological domains (i.e. insect counting as a biodiversity index). To meet a growing biological demand and to compensate a decreasing workforce amount, automated entomology has been around for decades. This challenge has been tackled by computer scientists as well as by biologists themselves. This thesis investigates the ways to classify different insect pests using various techniques. Generally these approaches undergo feature extraction, classification methods on the tested datasets. Although various techniques were proposed, transfer learning based methods are limited in literature which addresses the aforesaid problem. Presently two transfers learning based on CNN architectures were performed. The pre trained CNN models such as Alexnet and VGG16 were selected for our experiments. From the experimental results, it is observed that transfer learning can address this classification with minimal training requirements and the Alexnet is more effective in comparison to the VGG16 CNN model in terms of accuracy.**

Index Terms-- **CNN, Deep learning, Transfer learning, VGG16, Alexnet Classification.**

I. INTRODUCTION

Agriculture field is one of the central points that are identified with social steadiness and monetary improvement. Nonetheless, a few hundred distinct types of insects are discovered connected with put away grains and their items, and insects that assault our stores of oat sustenance constitute a standout amongst the most genuine dangers to our development. The manual grouping of such creepy crawly bothers in paddy fields can be tedious and requires generous specialized ability. The undertaking turns out to be all the more difficult when bug irritations are to be perceived from still pictures utilizing a mechanized framework. Pictures of one bug vermin might be taken from various perspectives, messed foundation, or may endure change, for example, revolution, commotion, and so forth.

A. CNN

In deep learning, a convolutional neural network (CNN or ConvNet) is a class of deep, feed-forward artificial neural networks, most commonly applied to analyzing visual imagery. CNNs have emerged from the study of brain's visual cortex. These type of deep neural nets have been used in image recognition since 1980s[9].

A CNN architecture is formed by a stack of distinct layers that transform the input volume into an output volume (e.g. holding the class scores) through a differentiable function. A few distinct types of layers are commonly used and they are convolutional layer, pooling layer, ReLU activation layer and fully connected layer [2].

Feature learning

It is the first part of the architecture which receives the image input and extracts important features. These important features are extracted using convolutional layers. The pooling layers are used for reducing the spatial dimensionality of the representation, saving a lot of computational power. and also reducing the risk of over fitting.

Classification

As the name suggests, in this part the input is the extracted features from the feature learning part which are used for training the fully connected layers for classification. The final fully connected usually outputs the prediction of the image.

B. Alex Deep Neural Network

Alex Net's design has 60,000 total parameters spread over eight layers. Three fully linked layers and five convolutional layers make up these eight layers. Other significant advancements include the use of multiple GPUs for training and the use of enhanced versions such as flipping, scaling, and noising of the pictures for training. Furthermore, the network employed ReLU (Rectified Linear Unit) activation functions instead of tanh (hyperbolic tangent), whichever helped minimize the network's training time and was a present solution to the "vanishing gradient" difficulty at the time. When constructing the feature map, the pooling layers

additionally introduce a stride of 4 pixels, implying that each of the local receptive fields overlapped, lowering their model's error considerably.

C. VGG16 Deep Neural Network

The VGG-16 network model is a convolution-based network model that is widely used in computer vision methods, and it performed well in the Image Net 2014 competition. For classification, we deleted the top layers of this model and re-placed them with Flatten, Dense, Drop, and dense-Soft Max layers. To avoid over fitting, the drop layer is utilized to drop certain values at random. The Soft Max layer is used for emotion classifications into many categories. Excepting the last layer, the ReLu activation function has been used in all of the layers.

TABLE I
Confusion matrix for binary classification

Ground Truth

Obtained		True	False
	True	TP	FN
	False	FP	TN

D. Figures and Tables

E. Proposed Transfer Learning

Transfer learning is a machine learning research issue that concentrated on storing and transferring proficiency learned while addressing one issues to a different but related issues.

Fig.1 Class specific accuracy for VGG16 and Alexnet transfer learning classifiers
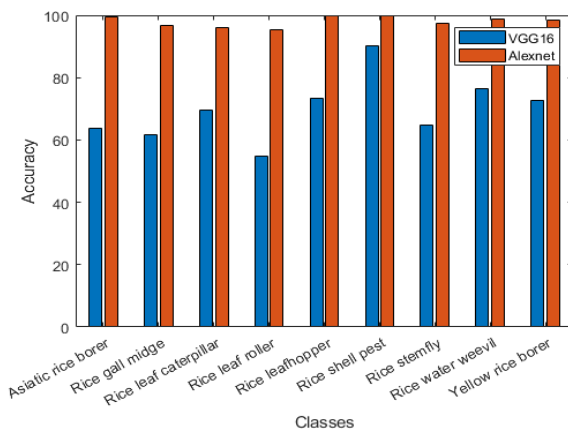
F. Dataset Description

The IP102 dataset contains more than 75,000 images belongs to 102 categories. A natural long-tailed distribution presents on it. In addition, we annotate 19,000 images with bounding boxes for object detection. The IP102 has a hierarchical taxonomy and the insect pests which mainly affect one specific agricultural product are grouped into the same upper-level category.

G. Performance Evaluators

For validation of the approach, 40% testing and 60% training samples are considered for each class randomly. The observation was replicated over 30 assessments and their mean calculations are shown. For contrasting the performance of various methods, the commonly used performance measures for multi class data sets like class specific Accuracy, Overall Accuracy (OA), κ, and Average Accuracy (AA) are listed in tables. Descriptions of the measures are presented below.

For ease of understanding the binary classification, the confusion matrix (CM) is presented in Figure 7.2. In the figure, columns represent the original class labels (supplied with the data) as *True* and *False*, similarly each row represents the outcome of the classifier.

True Positive (TP) and True Negative (TN) are defined as both the original (ground truth) and the obtained (classified) class labels are true and false respectively. While the contradictions are presented as False Positive (FP) and False Negative (FN) which are off-diagonal in the CM. Let, total N samples are tested which is equal to the

$$N = \Sigma (TP + TN + FP + FN).$$ So, higher the TP and TN values lead to a better accuracy; on the contrary, higher the FP and FN values reject the classifier.

II. ACKNOWLEDGMENT

III.CONCLUSION

This study facilitates the early diagnosis of plant diseases to prevent crop loss and the spread of diseases. The CNN model is used to predict different insect pests correctly. The performance of various pre-trained CNN models such as VGG,

Alexnet is observed, and then based on performance metrics, the Alexnet model is found to be more accurate. The model's testing is done using performance evaluation metrics such as overall accuracy, average accuracy, Kappa and loss. The Alexnet model achieved the highest accuracy of 98%. One of the main problems faced in a larger neural network is the vanishing gradient problem.

IV. REFERENCES

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