





TABLE I  
Confusion matrix for binary classification

**Ground Truth**

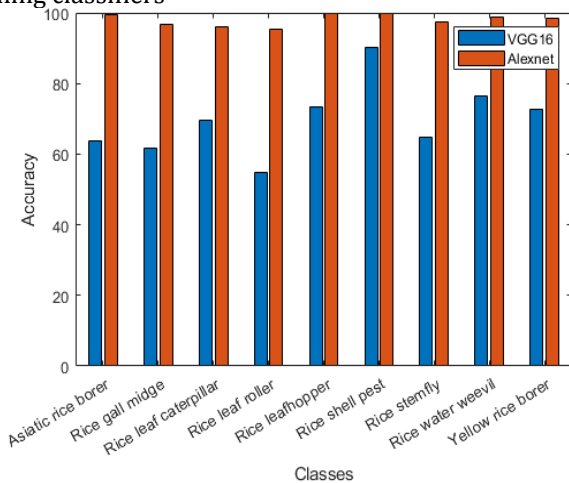
<b>Obtained</b>		<b>True</b>	<b>False</b>
	<b>True</b>	TP	FN
	<b>False</b>	FP	TN

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),  $\kappa$ , 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

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

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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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