PestID

Helping Farmers Identify Crop Pests

Problems with Traditional Approach for Pest Identification

PROBLEM 1

Manual - Requires continous monitoring of crops

PROBLEM 2

Time Consuming

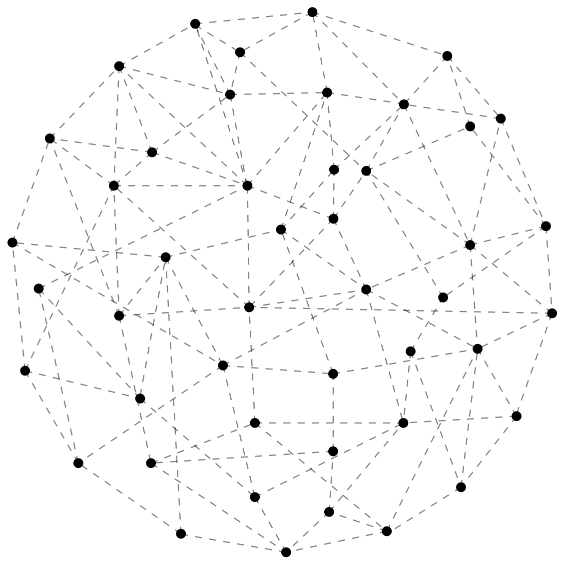
PROBLEM 3

Labor Intensive

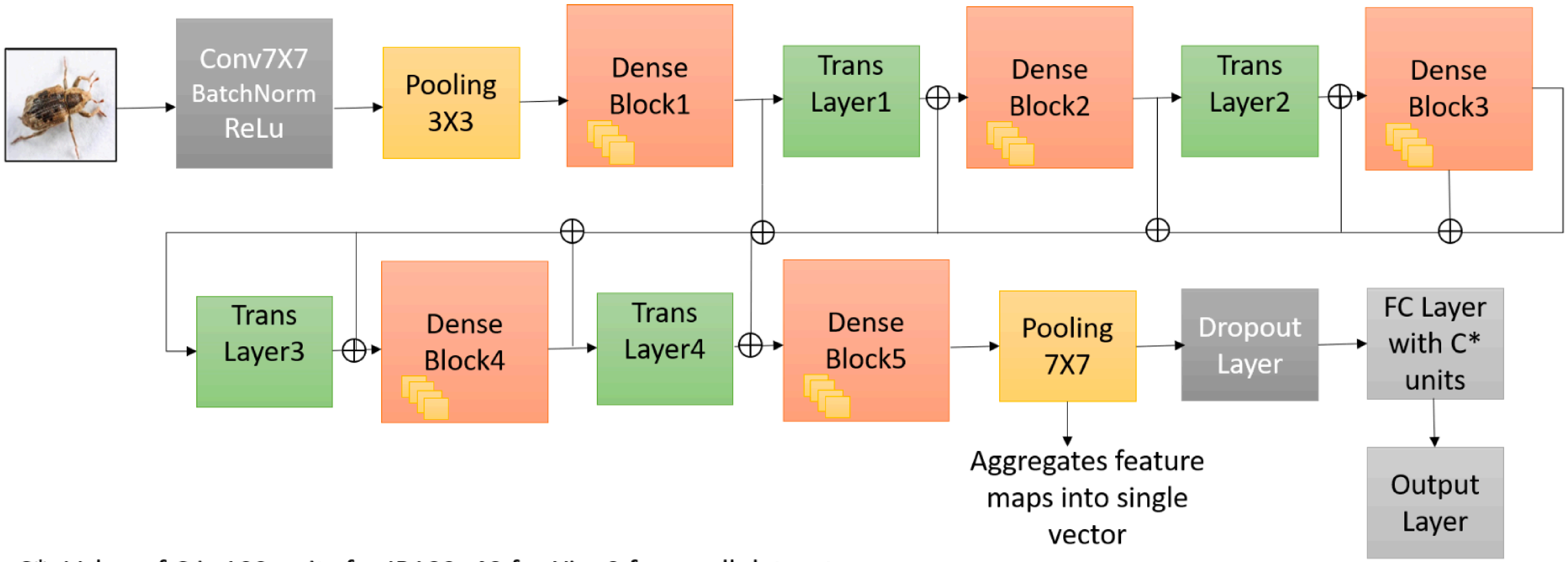
Innovation

Computerised Identification

Enhanced Deep Neural Network Architecture for better accuracy.



Proposed Approach



C*- Value of C is 102 units for IP102, 40 for Xie, 9 for small dataset

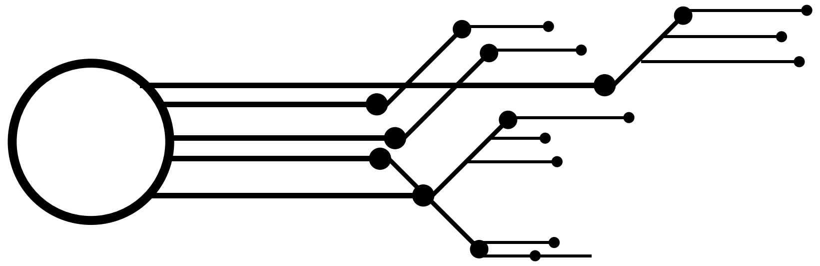
Each Dense Layer includes: Batch Normalization, ReLu, Conv3X3, Dropout Layer

Each Transition Layer includes: Batch Normalization, ReLu, Conv1X1, Dropout Layer, Pool2X2

Figure: Proposed Approach based on DenseNet 121

Enhancements

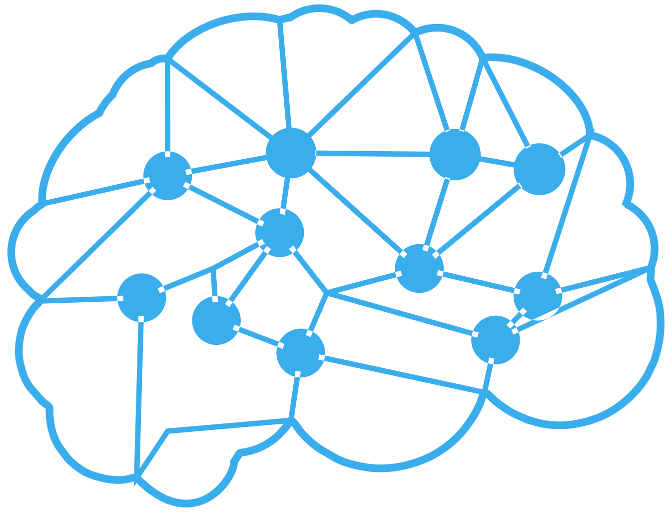
Number of Dense Blocks - 5 (compared to 4 in original) to increase depth and power of the model while combating overfitting. This was decided through hit and trial



Pooling 3X3 and 7X7 were used to have moderate and high spatial reduction respectively.

The compression factor, an attribute of transition block, was given a value of 0.7 to retain greater number of feature maps

A fully connected layer is added and the number of units to suit our datasets.



A transitional block was added corresponding to the new block

12 Dense Layers were kept in the additional dense block

Methodology

1. Worked with DenseNet architecture
2. No image pre-processing technique were used except image resizing
3. No complex data augmentation methods were used than standard augmentation techniques like rotation, shear and horizontal flip
4. For primary dataset, IP102 dataset was used since it was publicly available and consists of 75,222 images and 102 species of pests affecting 8 crops
5. Google Colab was used. We used cloud storage Google drive to store the images
6. We fine-tuned DenseNet121 to replace the last fully-connected layer of 1000 units to 102 units corresponding to IP102 dataset. This was done for comparison purposes
7. We froze the dense blocks of the base model to make them non-trainable and preserve their weight parameters. We then fine-tuned it again for the other 2 datasets Xie(40) and 9-class dataset from Kaggle.

Results

Model	IP102	Xie(40)	9-Class
ResNet50	56.16	54.02	50
DenseNet121	60	93.13	96.88
Proposed Approach	68.34	94.47	97.56

Conclusions

With the same approach used on all three dataset, IP102 dataset with 102 classes attained lowest accuracy as compared to the small dataset with only 9 classes (From Kaggle) that attained highest accuracy of the three dataset.

Therefore we can make out the following conclusions:

1. PestID can be good for tasks with limited training data.
2. With the increase in the number of classes in the dataset, performance seems to go downhill.