DANGEROUS FARM INSECTS CLASSIFICATION

COMP 263-003 Deep Learning - Centennial College

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Abstract—This project explores deep learning for agricultural insect classification using a limited dataset. An initial CNN exhibited overfitting. Data augmentation with a cGAN yielded modest improvement. Transfer learning with the InceptionResNetV2 architecture significantly boosted performance, demonstrating its effectiveness for small datasets.

Keywords—Insect, CNN, GAN, Transfer learning, Data augmentation

I. Introduction

The accurate and timely identification of dangerous insect pests is a critical component of effective agricultural management. Failure to correctly identify harmful insects can significantly hinder pest control efforts, ultimately leading to crop damage and economic losses. Traditional identification methods, often relying on manual inspection, can be time-consuming, labor-intensive, and prone to human error. To address these challenges, automated insect classification systems driven by deep learning techniques offer promising solutions.

This project utilizes the Dangerous Farm Insects Image Dataset to develop a robust deep learning-based classification system. This dataset contains 1591 high-quality images meticulously labeled with 15 classes of insects deemed particularly harmful to agricultural crops. The images in the dataset are predominantly in RGB format and possess an average resolution of 758x1015 pixels, providing sufficient detail for feature extraction by deep learning models. The dataset's balanced nature, with approximately 100 images per class, facilitates effective model training.

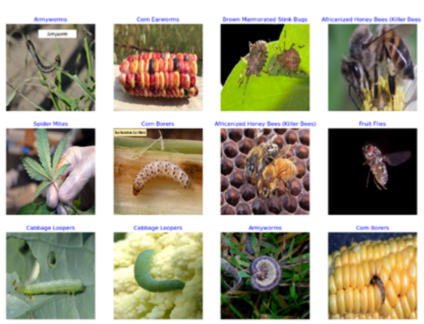

Fig 1 Images examples from the dataset

II. Methodology

Model 1: Supervised Learning - CNN

This project first employs a Convolutional Neural Network (CNN) for insect image classification. The CNN architecture adopts a sequential design, featuring stacked convolutional and max-pooling layers for progressive feature extraction. The model transitions to fully connected dense layers for classification, incorporating L2 regularization and dropout to mitigate overfitting. We use the Adam optimizer and sparse categorical cross-entropy loss function for training. Accuracy serves as the primary performance metric. Image data is transformed into NumPy arrays and preprocessed to match the model's input requirements. The model is trained over 30 epochs with a batch size of 32, using validation data to monitor generalization. Model performance is assessed on a held-out test set, with test accuracy plotted alongside validation accuracy. A confusion matrix provides a detailed breakdown of classification performance across individual insect classes.

Model 2: Unsupervised Learning-cGAN

The Conditional Generative Adversarial Networks (cGAN) we used in this project to augment datasets for image classification. The generator synthesizes images by integrating a noise vector with a label-specific embedded vector, using convolutional transpose and batch normalization layers, finalized by a 'tanh' activation. Concurrently, the discriminator enhances accuracy by merging label information with image data, processed through convolutional and dropout layers with LeakyReLU activation, to determine image authenticity.

The training utilized an alternating strategy to optimize both the generator and discriminator, improving their ability to produce and evaluate images respectively. Conducted over 50 epochs, this method effectively expanded our dataset for classifying hazardous farm insects, demonstrating cGANs as an effective tool for data augmentation under limited samples.

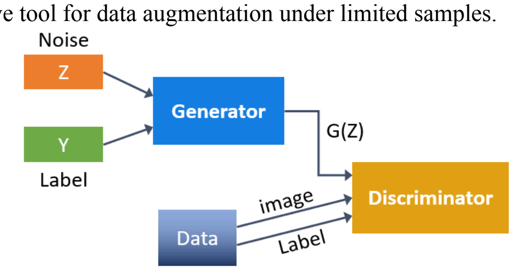

Fig 2. cGAN Architecture

Model 3: Transfer learning InceptionResNetV2

This project will employ the InceptionResNetV2 architecture, a model known for its exceptional image recognition capabilities. Its combination of inception modules and residual connections allows for comprehensive feature extraction without sacrificing performance as the network deepens. To capitalize on this, the project will leverage transfer learning by utilizing the model's pre-trained weights on the ImageNet dataset. The base convolutional layers will initially be frozen to preserve their learned representations, accelerating training and boosting accuracy. A custom top layer will be added to adapt the model for classifying the specific insect classes within the project's dataset. Selective retraining of this layer, and potentially a few from the InceptionResNetV2 base, will fine-tune the model. This strategic approach aims to increase both efficiency and overall classification performance.

III. Result

Model 1: Supervised Learning - CNN

The limited dataset size presented a challenge for our CNN model in generalizing beyond its training scope. While the model achieved a commendable training accuracy of roughly 70.9%, this did not translate effectively to unseen data, with validation and test accuracies at around 29.7% and 31.4%, respectively. Such a gap indicates a pronounced overfitting to the training set, where the model likely memorized specific training details rather than learning to generalize.

Given the small sample size, the model's ability to extract and learn from the underlying patterns was constrained, leading to a performance that did not robustly extend to the validation and test sets. The consistent gap between training and validation/test accuracies, despite the high training accuracy, further underscores the model’s overfitting and lack of generalization.

Model 2: Unsupervised Learning-cGAN

The integration of images generated by cGAN with the original dataset has resulted in certain improvements in the performance of the CNN model in insect classification. The CNN, trained on this augmented dataset, attained a training accuracy of approximately 88.8%, the validation and test accuracies also experienced an uptick, recorded at around 36.4% and 42.7%, respectively. This increment, while modest, indicates that the synthesized images from the GAN helped mitigate the overfitting observed in Model 1 by providing a more varied and extensive training sample, thereby enhancing the CNN’s generalization capabilities to some extent.

The results affirm the potential of using GAN-generated images to enrich limited datasets, thus boosting model performance. The observed enhancement validates our unsupervised learning approach as a viable path toward improving classification accuracy in scenarios constrained by sample size.

Model 3: Transfer learning InceptionResNetV2

Utilizing the InceptionResNetV2 architecture with transfer learning techniques significantly enhanced our model's accuracy. Despite the limited dataset size of our project, the model achieved a training accuracy of 99%. This high accuracy suggests that the model was able to learn detailed features from the training data effectively. The validation and test accuracies, at 72% and 79% respectively, are indicative of a substantial improvement in the model's ability to generalize when compared to model 1 and model 2.

The successful application of InceptionResNetV2 for our dataset, which is relatively small for deep learning standards, underscores the advantage of transfer learning in leveraging pre-trained networks. By using a model pre-trained on a much larger and diverse dataset (ImageNet), our model gained a rich, transferable feature representation that provided a strong foundation for accurate classification, despite the constraints of the dataset size.

IV. Conclusion

In this project, we addressed the challenge of classifying insects with a limited dataset using three different deep-learning models. The CNN model exhibited overfitting, as evidenced by high training accuracy but lower validation and test scores. Incorporating cGAN for data augmentation improved generalization slightly. However, the most significant improvement came with the implementation of the InceptionResNetV2 architecture through transfer learning. This model achieved high accuracy on both training and unseen data, highlighting the efficacy of transfer learning in handling small datasets. These findings reinforce the importance of using pre-trained models and data augmentation to enhance performance in data-constrained environments. Future work should continue to explore these methods to further reduce overfitting and improve model generalization.

V. Contribution

A. Katiraee meticulously preprocessed and analyzed the dataset, ensuring its quality for modeling and providing insights for later decisions. Y. Shen developed the cGAN model, generating high-quality images to augment the dataset. H. Jetti deployed a state-of-the-art model using transfer learning, accelerating training, and improving accuracy. P. Goel designed and implemented the Convolutional Neural Network (CNN) crucial for image classification. All team members maintained thorough documentation throughout the project.

VI. Reference

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