



Original Article

DenseNet121 based pest identification in plants

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ARTICLE INFORMATION



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ABSTRACT

Smart agriculture has benefited greatly from the widespread use of deep learning, which has proven critical to the industry. Reliability of data annotation and poor data quality, on the other hand, will severely limit the performance of intelligent applications because deep learning models are limited by these factors. We approaches, distance-entropy to distinguish the good and bad data from the perspective of information. DenseNet-121 was used as the backbone network and the IPO6 dataset was used in trials. The findings highlight the frequency of duplicate data by demonstrating that almost 50% of the dataset has sufficient redundancy to produce test accuracy scores that are comparable. In addition, a thorough examination of representative samples resulted in the development of recommendations for enhancing dataset efficiency. These recommendations provide a useful road map for data-driven smart agriculture research, advancing knowledge and the use of data to advance agricultural innovation and sustainability.

Keywords: Deep learning; Pest; CNN; Distance entropy; Plants

1. Introduction

Smart agriculture is increasingly driven by advances in sensing, embedded computing, Internet of Things (IoT) infrastructures, and artificial intelligence (AI), enabling continuous monitoring of crop conditions, optimized input utilization, and timely responses to environmental stressors (Muangprathub et al., 2019; Sivanantham et al., 2022). In parallel, the availability of low-power sensor networks and edge-capable platforms has accelerated real-time decision support and field automation, making data-driven plant protection a practical requirement rather than a research prototype. Among AI techniques, deep learning has become central to visual recognition tasks in agriculture, including pest detection, disease identification, and autonomous navigation (Li et al., 2020; Yang et al., 2022). Despite strong performance in controlled benchmarks, practical deployment remains constrained by the difficulty of acquiring and labeling high-quality images under diverse field conditions. Uncontrolled illumination, motion blur, background clutter, and occlusions introduce substantial variability, making annotation slow, expensive, and prone to inconsistency. Consequently, model accuracy and reliability often depend as much on dataset quality as on network architecture.

A recurring challenge in pest identification is that performance improvements do not scale proportionally with dataset size. Many publicly available pest datasets

contain redundant samples or weakly informative images that contribute little to representation learning, leading to diminishing returns in accuracy while increasing training cost. This observation has motivated interest in data-efficient learning strategies, including few-shot and meta-learning approaches that reduce dependence on large labeled datasets. For example, Relation Networks enable metric-based comparison between query samples and a limited labeled support set (Sung et al., 2018), while meta-learning methods can improve adaptation under sparse labels (Li & Yang, 2021). Although these methods address label scarcity, they do not explicitly quantify redundancy or identify which samples are most beneficial for training in a given dataset.

To improve data utility, recent studies have shifted from collecting more samples to selecting better samples. Active learning methods such as Learning Loss estimate which unlabeled examples are likely to improve performance if annotated (Yoo & Kweon, 2019). In addition, entropy-based criteria have been explored to measure uncertainty and informativeness in feature space, enabling systematic screening of redundant or low-value samples (Li et al., 2023; Li & Chao, 2022). In agricultural vision, such selection principles are especially relevant because labeling requires domain expertise and large-scale data collection is costly.

In the plant protection context, deep learning has been widely applied for pest and disease recognition.

Ahmed et al. (2021) reported CNN-based pest detection pipelines that reduce manual inspection effort, while Rawat & Singh (2024) demonstrated robust disease classification using transfer learning. More recently, Negi et al. (2024) highlighted dataset redundancy in agricultural image collections and motivated the need for learning-centric data quality assessment. These works collectively indicate that improving dataset efficiency is a key step toward scalable and deployable pest recognition systems.

Motivated by these gaps, this study focuses on sample informativeness as a primary factor in pest classification performance. Instead of expanding training data indiscriminately, we evaluate which samples contribute meaningful learning value using a distance-entropy (Proto-DE) criterion computed from embeddings learned by a DenseNet121 backbone. By ranking samples

according to their informativeness relative to class prototypes, the proposed framework supports compact dataset construction, reduces labeling and training overhead, and maintains high classification accuracy.

The main contributions of this paper are threefold: (i) We demonstrate empirically that increasing dataset size yields limited gains when redundancy is high, motivating a quality-driven data strategy for pest recognition. (ii) We apply a distance-entropy-based informativeness measure in embedding space to prioritize samples that are likely to refine decision boundaries and improve generalization. (iii) We present a structured analysis of informative versus less informative subsets, providing practical guidance for building compact yet effective pest image datasets for smart agriculture applications.

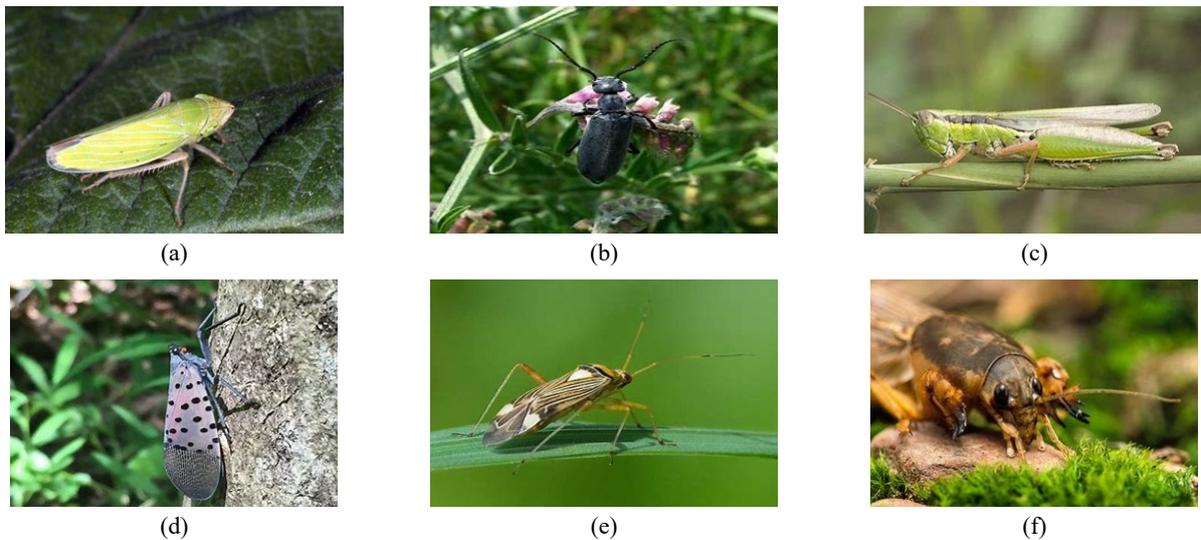


Figure 1. Insect samples, IPO6 Dataset, (a) Cicadellidae, (b) Legume blister beetle, (c) Locustoidea, (d) *Lycorma delicatula*, (e) Miridae, (f) Mole cricket.

2. Materials and Methods

2.1. Dataset Description

To ensure reliable and computationally efficient pest classification, we curated a balanced dataset derived from a large-scale public agricultural pest dataset originally introduced by Wu et al. (2019). The original dataset comprises over 75,000 images spanning 102 categories. However, it suffers from several quality issues, including mislabeled samples, image watermarks, significant intra-class variation, and pronounced class imbalance—factors that adversely affect both model performance and training efficiency.

To address these challenges, we selected six distinct pest classes and constructed a refined and balanced dataset named IPO6. Each class in the IPO6 dataset contains 1,000 RGB images of size $84 \times 84 \times 3$, resulting in a uniform distribution across categories. This preprocessing step ensured that the dataset was free from label noise and visual artifacts while maintaining sufficient inter-class diversity. Additionally, to facilitate model evaluation, 10% of the images (*i.e.*, 100 samples per class) were randomly selected as the test set, with the remaining samples used for training. Figure 1 presents representative image samples

from each class, and Table 1 provides detailed class-wise statistics of the curated IPO6 dataset.

Table 1. The classes and amounts of IPO6.

IPO6 Dataset	Name	Train	Test
Classification 0	Cicadellidae	900	100
Classification 1	Legume blister beetle	900	100
Classification 2	Locustoidea	900	100
Classification 3	<i>Lycorma delicatula</i>	900	100
Classification 4	Miridae	900	100
Classification 5	Mole cricket	900	100

2.2. Proposed Methodology

2.2.1. Backbone Network Architecture

In recent years, the depth and complexity of convolutional neural networks (CNNs) have grown substantially, driven by continuous architectural innovations and advancements in computational resources. Notable deep models such as VGG-19, ResNet-101, and ResNet-152 have introduced hundreds of convolutional layers, achieving remarkable success across various vision tasks. However, as noted by Li et al. (2020) excessively deep architectures are susceptible to overfitting, especially when applied to relatively simple or low-complexity datasets.

Given the moderate complexity of the IPO6 dataset used in this study, a shallow yet efficient network is more appropriate. Therefore, we adopt a modified version of DenseNet-121 by Huang et al. (2017), configured with four convolutional blocks to achieve a balance between performance and computational efficiency. Each convolutional block consists of 3×3 convolutional layers followed by 2×2 max-pooling. To enhance convergence and generalization, each layer is equipped with batch normalization and ReLU activation functions. A schematic overview of the network architecture is illustrated in Figure 2.

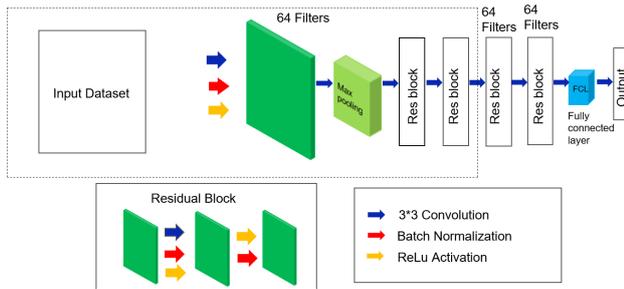


Figure 2. DenseNet121 backbone network's architecture.

The key innovation behind DenseNet lies in its dense connectivity pattern, where each layer receives feature maps from all preceding layers. As highlighted by He et al. (2016), such architectural design mitigates the vanishing gradient problem by facilitating feature reuse and promoting gradient flow during backpropagation. This characteristic makes DenseNet not only computationally efficient but also highly effective for extracting robust features even in shallower configurations. Consequently, DenseNet-121 is well-suited as the backbone for our pest classification framework.

This study introduces a distance entropy-based framework for evaluating and selecting high-quality training samples in the context of pest identification using deep learning. The methodology is centered on the Distance Entropy (Proto-DE) concept proposed by Li & Chao (2022), which measures a sample's informativeness based on its spatial distance from class prototypes in the embedding space. Rather than relying on visual image quality, this approach emphasizes the informative value of a sample—defined by its contribution to improving the model's learning performance.

The process begins by dividing the dataset into two subsets: Ebase, containing initial training samples, and Eselect, consisting of unlabeled or candidate samples. A convolutional neural network (CNN) is first trained on Ebase to learn initial feature representations. Once trained, the model is used to extract embeddings for samples in Eselect. These embeddings are analyzed using the Proto-DE strategy, which computes the distance of each sample from class prototypes to estimate its potential informativeness.

In Proto-DE, the final classification layer of the network is replaced with a two-neuron fully connected layer that outputs 2D feature embeddings. These compressed representations allow for better visualization and clustering while preserving class-discriminative information. Class prototypes are computed as the average

embeddings of samples within each class. The distance of each candidate sample from these prototypes is then calculated and normalized using a softmax-like function. The resulting distribution is used to compute entropy, which reflects how ambiguously the sample fits into the existing class structure. A higher entropy value indicates that a sample is near decision boundaries and carries more informative value for learning. Samples from Eselect are iteratively added to Ebase based on their entropy scores, allowing the model to incrementally learn from the most valuable data. This sample-efficient selection process continues until the training set reaches a predefined size or performance threshold.

Overall, the proposed methodology enables the creation of compact yet highly informative training datasets, reduces data redundancy, improves generalization, and enhances the robustness of pest identification models—particularly in resource-constrained agricultural environments where data collection and labeling are expensive. From a representation learning perspective, samples with high distance entropy tend to lie near regions of class overlap in the learned embedding space, where gradient updates contribute most effectively to refining decision boundaries. In contrast, low-entropy samples are typically concentrated near class prototypes and provide largely redundant gradient information. As a result, prioritizing high-entropy samples accelerates learning during early and intermediate training stages, while performance gains naturally saturate once the dataset becomes sufficiently representative.

2.2.2. Novelty of the Proposed Method

Unlike conventional uncertainty-based or probability entropy methods that rely on classifier output confidence, the proposed distance-entropy framework evaluates sample informativeness directly in the embedding space learned by the backbone network. By measuring the relative distance of samples to class prototypes, the method captures geometric ambiguity near decision boundaries, rather than prediction uncertainty alone. This allows the framework to distinguish between redundant high-confidence samples and truly informative boundary samples, a limitation observed in traditional entropy and active learning schemes. As a result, distance entropy provides a learning-centric assessment of data quality that is explicitly aligned with representation learning dynamics.

3. Results

To validate the effectiveness and robustness of the proposed distance entropy-based sample selection method, a series of controlled experiments were conducted. These experiments focused on analyzing the influence of feature embedding dimensionality and the initial training dataset size on model performance. The goal was to assess how well the method identifies informative samples and contributes to improved classification accuracy in pest detection tasks. All experiments were executed on a computing platform equipped with an NVIDIA TitanXp GPU (12GB VRAM). The implementation was carried out using Python in a Google Colab environment, leveraging standard deep learning libraries including TensorFlow, Keras, and NumPy. The computational setup ensured reproducibility

and consistency across trials while accommodating the iterative training and evaluation loops inherent in the distance entropy framework. To improve evaluation robustness, all experiments were repeated three times using different random initializations, and the reported results correspond to average values across runs to mitigate stochastic bias. Model performance was assessed using test accuracy, training–validation convergence behavior, and relative performance gains across incremental training stages, enabling a consistent and controlled comparison of sample selection strategies.

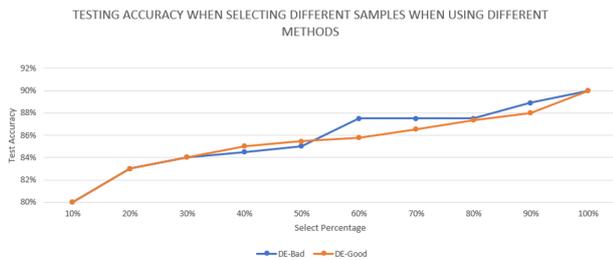


Figure 3. Test accuracy of the proposed method on IP06 dataset.

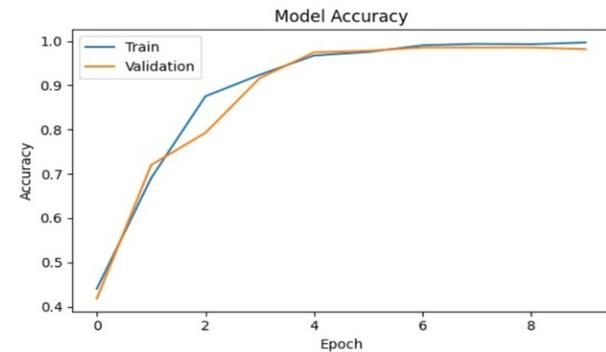


Figure 4. Training and validation accuracy.

3.1.1. Effectiveness of Distance Entropy-Based Selection

In alignment with the proposed methodology, we ranked dataset samples based on their informativeness scores using the distance entropy metric. At each experimental iteration, the top-ranked informative samples were progressively added to an initial base training set. Simultaneously, a comparative control experiment incorporated the least informative samples to examine the performance gap between high- and low-quality data subsets. This comparative design serves as a controlled evaluation of sample quality, in which the effect of data informativeness is isolated while keeping the network architecture, training protocol, and optimization settings fixed. By contrasting high-entropy (informative) samples with low-entropy (least informative) samples under identical conditions, the analysis directly quantifies the contribution of sample selection to learning performance. This controlled setup enables a rigorous assessment of how sample informativeness influences convergence behavior and classification accuracy.

To ensure robustness, all experiments were repeated three times, with average values reported. Each iteration added 10% of the dataset to the base class, producing a total of nine incremental training stages.

Neutral samples were intentionally omitted to isolate the comparative impact of informative versus redundant data. The results were revealing. When selecting high-entropy (informative) samples, a 90% test accuracy was achieved using only 50% of the available dataset. Conversely, using the complete dataset improved accuracy only marginally to 92.04%, confirming the hypothesis that a significant portion of the dataset contributes little to learning. This result illustrates the efficacy of prioritizing sample quality over quantity.

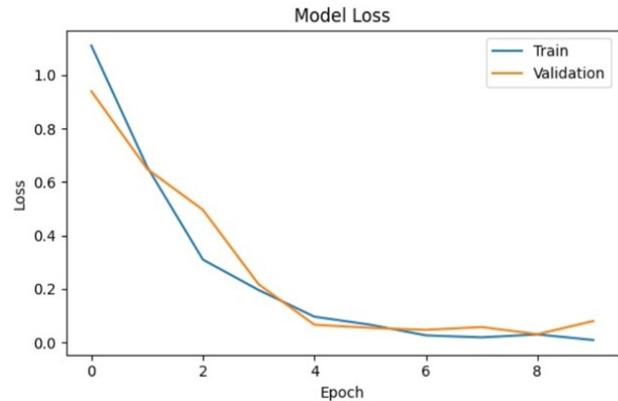


Figure 5. Training and validation loss.

Figure 3 illustrates this trend, where models trained with informative samples consistently outperformed those trained on lower-quality data, especially within the 30–60% training range. Accuracy differences in this range reached as high as 7.43%. During the early training phase (10–30%), accuracy diverged rapidly, primarily due to underrepresentation by the bad sample group. In the later stages (70–100%), performance gains tapered off, indicating dataset saturation.

Further insights are drawn from training and validation accuracy plots (Figure 4) and loss curves (Figure 5). High training and validation accuracy suggest effective learning and generalization, while closely aligned loss curves help confirm minimal overfitting. Table 2 provides a comprehensive summary of the training and testing configurations, confirming the reliability and reproducibility of our findings.

Table 2. Training loss and accuracy.

Epochs	Loss	Accuracy (%)	Val Loss	Val Accuracy (%)
1	1.11	44.0	0.94	48.8
2	0.65	69.0	0.64	78.0
3	0.31	87.5	0.49	79.2
4	0.19	92.3	0.21	91.6
5	0.09	96.7	0.06	97.4
6	0.066	97.5	0.05	97.8
7	0.026	99.0	0.04	98.5
8	0.019	99.3	0.05	98.5
9	0.030	99.2	0.03	98.5
10	0.001	99.6	0.08	98.1

3.1.2. Summary of Key Findings and Limitations

The experimental results demonstrate that the proposed distance entropy-based sample selection strategy significantly improves data efficiency in pest classification tasks. By prioritizing high-entropy (informative) samples,

the model achieves approximately 90% test accuracy using only 50% of the training data, while utilizing the full dataset yields only a marginal improvement to 92.04% accuracy. This confirms that a substantial portion of the dataset is redundant and contributes limited additional learning value.

The observed accuracy gains are most prominent in the 30–60% training range, where informative sample selection outperforms low-quality data by up to 7.43%, highlighting the effectiveness of the proposed approach during data-scarce training phases. Furthermore, closely aligned training and validation curves indicate stable convergence and minimal overfitting, demonstrating the robustness of the learning process.

Despite these advantages, the current study has certain limitations. The experiments are conducted on a curated dataset with six pest classes, and performance may vary when applied to larger or more diverse datasets with severe class imbalance. Additionally, the distance entropy computation relies on feature embeddings learned by the backbone network, which may be sensitive to network architecture and hyperparameter choices. Future work will focus on extending the proposed framework to larger-scale datasets, evaluating cross-dataset generalization, and integrating adaptive thresholding strategies to further improve robustness under real-world agricultural conditions.

4. Discussion

The proposed distance entropy framework demonstrates a strategic shift in data evaluation, particularly within intelligent plant protection systems that face long-tailed distributions and costly data acquisition. In such domains, the scarcity of rare class data complicates the ability of deep learning models to generalize effectively (Sung et al., 2018). Our method addresses this by focusing on sample informativeness—prioritizing those that contribute meaningful variance and decision boundary refinement.

This approach also critiques the limitations of traditional image quality assessment (IQA) (Borse & Markad, 2014), which emphasizes visual fidelity (e.g., compression artifacts, perceptual quality) without considering the semantic contribution of samples to learning algorithms. While these visual metrics may be suitable for compression or perceptual consistency, they fall short in optimizing model training efficiency (Preedanan et al., 2018).

Rawat & Singh (2024) demonstrated robust apple leaf disease classification using transfer learning. Negi et al. (2024) used RESNET-50 based methodology for pest identification in plants. Ahmed et al. (2021) reported CNN-based pest detection pipelines that reduce manual inspection effort. By contrast, in this paper, we have proposed DenseNet121 based method for pest identification in plants. Also, the proposed method introduces an algorithm-aware metric that directly evaluates the training utility of samples. This allows for a smarter dataset construction strategy—yielding better generalization with fewer samples and reducing redundant computation and storage costs. The observed performance gaps in our experiments support the utility of this method

for real-world agricultural applications where both data volume and quality vary significantly.

Ultimately, this study advocates for a paradigm shift in data evaluation—from visually driven metrics to learning-centric data quality assessments—which can drive more scalable and effective implementations of smart agriculture systems.

5. Conclusion

In this paper, we proposed a distance-entropy-based method for evaluating and selecting informative training samples for agricultural pest classification. The approach leverages feature embeddings from a DenseNet121 backbone to quantify sample informativeness based on their distribution relative to class prototypes. This strategy enables the identification of high-quality data points that significantly contribute to model learning. Experimental results demonstrate that the proposed method achieves high classification accuracy with only a fraction of the total dataset, highlighting its efficiency in reducing redundancy while maintaining performance. The ability to consistently distinguish between informative and less useful data across various training conditions underscores the robustness of the approach. Overall, this work provides a practical and scalable solution for improving data efficiency in smart agriculture, particularly in scenarios where data labeling is costly or limited.

Despite its effectiveness, the proposed framework has certain limitations. The current evaluation is conducted on a curated dataset with a limited number of pest classes, and performance may vary for larger, more diverse, or highly imbalanced datasets encountered in real-world agricultural settings. Additionally, the distance entropy measure depends on feature representations learned by the backbone network, which may be influenced by architecture selection and training conditions. Future work will focus on extending the framework to larger-scale and multi-crop datasets, evaluating cross-dataset generalization, and exploring adaptive or architecture-agnostic entropy formulations to further enhance robustness and applicability.

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