Position-Sensitive Neural Networks for Insect Detection and Grain Quality Prediction in Storage

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Abstract- *Insect infestations in grain can lead to significant losses in both quantity and quality, impacting crop value. These insects not only consume grain but also contaminate it with their metabolic by-products and body parts, contributing to the growth of microflora and the creation of hotspots due to the heat and moisture generated by their activity. Severely infested grains are unsuitable for seed purposes and their products are unfit for human consumption. As such, effective monitoring and detection of stored-product insects is crucial. Recent advancements in hardware computing have led to notable progress in deep learning-based computer vision techniques for object detection, including the detection of insects on grain surfaces. Many grain depots now utilize high-definition cameras and insect-monitoring systems that capture images or videos, offering a practical opportunity for deep learning models to assist in detecting insect infestations. This project proposes an enhanced neural network architecture based on Incremental Learning Networks to detect and classify eight common stored grain insect species and predict grain severity. The proposed architecture incorporates a neural network for feature extraction, a region proposal network, and a position-sensitive score map for improved target detection. By integrating a position-sensitive score map in place of some fully connected layers, the network becomes more adaptable to complex backgrounds, enabling faster and more accurate insect detection. This innovative architecture also introduces position-sensitive ROI pooling to further improve performance. Experimental results demonstrate that the proposed model significantly outperforms existing models, achieving higher precision-recall rates for insect detection in grain images. The proposed solution offers an effective and efficient method for monitoring insect infestations in stored grain, ensuring better crop quality and minimizing losses.*

Keywords- Stored product insects, Insect detection, Convolutional neural networks, Deep learning, Incremental learning, Grain quality prediction, Instance segmentation, Agricultural technology

I. INTRODUCTION

Stored product insects pose a major threat to the quality and safety of stored food products, particularly grains, cereals, and dried fruits. These insects not only consume the stored products but also contaminate them with waste, body parts, and by-products, leading to reduced nutritional value, spoilage, and increased risk to human health. The issue is further compounded as these insects rapidly reproduce and adapt to storage conditions, making detection and control challenging.

Traditional methods such as visual inspection, probe sampling, and the use of pheromone traps are labor-intensive, subjective, and not suitable for large-scale industrial use. Additionally, these conventional approaches often fail to detect early-stage or internal infestations, leading to delayed responses and greater losses.

In recent years, advancements in artificial intelligence and computer vision have paved the way for more accurate and automated pest detection methods. Among these, deep learning models—particularly Convolutional Neural Networks (CNNs)—have shown great potential for identifying insect infestations from grain images. However, the variability in insect species, life stages, and grain conditions can reduce model accuracy.

This research proposes an enhanced neural architecture based on Incremental Learning Convolutional Neural Networks (IL-CNN) for effective and real-time insect detection and classification in stored grains. The IL-CNN model is designed to adapt continuously to new data while preserving prior knowledge, allowing it to operate efficiently in changing environments. By incorporating region proposal networks, position-sensitive score maps, and instance segmentation techniques, the system aims to accurately detect and quantify insects, even in complex and cluttered backgrounds.

The proposed solution addresses critical gaps in current pest detection methods by offering a scalable, accurate, and user-friendly system, suitable for integration with grain storage monitoring technologies. This system ensures timely interventions, reduces losses, and helps maintain food quality standards across the supply chain.

II. IDENTIFY, RESEARCH AND COLLECT IDEA

Early and accurate detection of stored product insects is essential for preventing grain spoilage, maintaining quality, and minimizing post-harvest losses. Traditional detection methods, while historically useful, are increasingly inadequate in addressing the complexity, scale, and precision required in modern grain storage systems. This section explores the challenges in current practices and presents the motivation for adopting intelligent, automated systems using advanced image analysis and machine learning.

2.1 Challenges in Conventional Insect Detection Methods

Traditional grain inspection relies heavily on visual examination, probe sampling, and pheromone-based traps. These methods are labor-intensive, time-consuming, and lack sensitivity, especially in detecting insects at early or hidden life stages. Techniques like X-ray imaging and electronic noses offer some improvement but are cost-intensive and require specialized equipment and trained personnel, making them impractical for widespread deployment in storage environments.

2.2 Limitations of Manual Image Interpretation

While machine vision systems have been employed to improve efficiency, their reliance on rule-based algorithms and handcrafted features limits their adaptability. Variations in grain type, lighting, and insect appearance can significantly affect detection accuracy. Moreover, distinguishing between debris, shadows, and insect features in real-world storage conditions remains a significant hurdle.

2.3 Need for Automation and Scalability

As grain storage operations scale up, the volume of data to be processed exceeds the capacity of manual inspection. There is a pressing need for a fully automated detection pipeline that can process images in real time, handle large datasets, and operate with minimal human intervention. Automation not only accelerates the inspection process but also standardizes it, eliminating subjectivity and variability in results.

2.4 Rise of Deep Learning in Object Detection

Deep learning techniques, particularly Convolutional Neural Networks (CNNs), have revolutionized object detection in computer vision. Unlike traditional image processing approaches, CNNs can learn hierarchical features directly from raw images, making them more robust to noise, scale variations, and overlapping objects. This adaptability is critical in detecting diverse insect species at different life stages in cluttered grain images.

2.5 Justification for Incremental Learning Architectures

The dynamic nature of grain storage—where insect populations evolve over time—demands a system that can learn continuously. Incremental Learning Convolutional Neural Networks (IL-CNNs) meet this requirement by updating their weights as new data becomes available, without forgetting previously learned patterns. This ensures that the detection system remains accurate even as environmental conditions and infestation patterns change.

III. PROPOSED SYSTEM

This research introduces a deep learning-based detection and prediction system specifically designed to address the challenges of stored product insect infestation in grain storage environments. The system is engineered to automate the identification of insects and assess grain quality, providing rapid and reliable analysis without the need for manual inspection. By leveraging the capabilities of convolutional neural networks—particularly an Incremental Learning Convolutional Neural Network (IL-CNN)—this model supports real-time monitoring, precise segmentation, and classification of insect species under various storage conditions. The system aims to support warehouse operators, quality inspectors, and agricultural decision-makers by delivering consistent and interpretable detection results, even in complex, noisy backgrounds such as bulk-stored grain.

3.1 Image Collection and Dataset Preparation

The effectiveness of the proposed system is rooted in the quality and diversity of the insect dataset. A collection of images was curated to represent common stored product insects such as Sitophilus oryzae, Tribolium castaneum, and Cyptolestes ferrugineus. These images were gathered from synthetic datasets and real storage environments, ensuring variability in grain types, lighting conditions, and infestation severity. Images were labeled with species names and infestation zones to enable supervised training. To ensure balance across classes, the dataset included a controlled mix of insect-free and infested grain samples. Each image was resized to a standardized resolution of 512×512 pixels, and pre-annotation was done using bounding boxes and segmentation masks. Anonymization of source data was maintained where applicable, and datasets were partitioned into training, validation, and testing sets with a focus on maintaining representative distribution across classes and environments.

3.2 Image Preprocessing

Given the variability in grain texture, color, and lighting in storage images, preprocessing plays a critical role in improving model input quality. The preprocessing pipeline begins with the conversion of RGB images to grayscale to reduce computational complexity and normalize visual features. Image denoising is performed using a bilateral filter to preserve edge details while minimizing grain-induced noise. Standardization through resizing ensures compatibility with the IL-CNN input requirements. Threshold-based binarization techniques are used to enhance contrast between insects and background grains. Region of Interest (ROI) localization is improved by applying soft Non-Maximum Suppression, which merges overlapping proposals while maintaining individual insect distinction. These steps help ensure that the model receives clean and informative input for optimal learning and accurate predictions

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3.3 Feature Extraction Using IL-CNN

The backbone of the proposed model is the Incremental Learning Convolutional Neural Network (IL-CNN), an enhanced architecture designed for adaptability and high-resolution segmentation. The network is composed of multiple convolutional layers responsible for learning spatial hierarchies, texture gradients, and shape outlines from preprocessed images. A Region Proposal Network (RPN) is integrated to generate candidate bounding boxes around potential insect regions, and position-sensitive score maps are used to improve fine-grained spatial accuracy during classification. These score maps replace the fully connected layers typically used in traditional CNNs, allowing the system to distinguish insects from background noise even in densely packed or partially obscured images. Position-sensitive ROI pooling is also implemented to preserve detailed localization, which is crucial for identifying insects of varying size and shape. This combination of architectural components allows the IL-CNN to achieve strong performance even in cluttered, low-contrast grain images.

3.4 Model Training and Validation

The IL-CNN model is trained on the curated dataset using a supervised learning approach. During training, the system is exposed to annotated examples, gradually learning to associate insect patterns with specific class labels. Data augmentation techniques—including horizontal flipping, brightness shifting, and random cropping—are applied to artificially expand the training set and improve model generalization across unseen samples. Transfer learning is employed using pre-trained CNN weights to speed up convergence and enhance feature extraction performance. The model is validated using a reserved dataset, and performance metrics such as precision, recall, F1-score, and mean Average Precision (mAP) are calculated. The model's predictions are also visually verified using segmentation overlays to assess whether the detected insects match their actual positions and classifications. Results from the validation phase demonstrate high detection rates, low false positives, and consistent segmentation accuracy, supporting the suitability of the IL-CNN for deployment in storage inspection tasks.

3.5 Insect Detection and Output Interpretation

Once trained, the system is deployed to evaluate real-time grain images uploaded via a web interface. Upon receiving an image, the system automatically detects the presence or absence of insects, identifies the species, and estimates the severity of infestation. Visual feedback is generated using bounding boxes and mask overlays to indicate the position and extent of insect presence. In addition to detection results, the system outputs quantitative data such as insect count and surface coverage ratio, aiding in grain quality assessment. The architecture supports interpretability features that allow users to understand how predictions are made, increasing transparency in AI-assisted decision-making. In cases of uncertainty or low-confidence detections, the system flags the image for manual review, reducing the risk of false negatives in critical scenarios.

3.6 Deployment and Practical Integration

To make the system accessible and easy to use, it is developed as a web-based application using Flask and integrated with a MySQL database for backend operations. The front-end interface, built with HTML, CSS, and Bootstrap, supports both admin and end-user functionalities. Administrators can manage datasets, initiate model training, and configure insect classification rules, while users can upload grain images and receive instant analysis. The lightweight nature of the application ensures that it can run on standard computing setups without the need for high-end hardware. The modular design also allows future integration with storage facility management systems and IoT-enabled cameras for automated monitoring. The system supports continual learning, enabling it to adapt to new insect species or storage conditions over time, thus future-proofing it for long-term agricultural use.

IV. SYSTEM DESIGN

The system architecture designed for stored product insect detection and grain quality prediction adopts a modular, scalable pipeline that ensures both high detection performance and real-world usability in agricultural storage environments.

It is engineered to transition seamlessly from raw grain image input to interpretable output, including insect classification, severity assessment, and grain condition analysis. Each component plays a distinct role, collectively enhancing the speed, reliability, and precision of the detection process. The architecture consists of six core stages: input acquisition, preprocessing, feature extraction, model training, prediction, and final deployment.

4.1 Input Image Acquisition

The system begins its operation by ingesting stored grain images captured through high-resolution cameras or extracted from precompiled datasets. These images contain both insect-infested and clean grain samples, offering diversity in background textures, grain types, and lighting conditions. The system supports common image formats such as JPEG and PNG, allowing for easy compatibility with standard digital imaging tools and smartphones. To accommodate both offline inspection and real-time surveillance, the design supports batch uploads as well as live image streaming via web-based or IoT camera interfaces.

4.2 Preprocessing Module

Once acquired, the images undergo a structured preprocessing routine designed to reduce visual noise, standardize format, and isolate key features. Initial preprocessing involves conversion to grayscale, followed by bilateral filtering to preserve edge structures while minimizing background grain noise. Histogram equalization is applied to enhance contrast between insects and grain surfaces. Threshold-based binarization segments the regions of interest, focusing the detection process on the foreground where insects are likely to appear. These preprocessing operations collectively improve the clarity and consistency of the input data, making it more suitable for robust feature learning by the neural network.

4.3 Feature Extraction Unit

The next critical phase involves feature extraction using convolutional neural network layers that are capable of learning spatial hierarchies from image data. Unlike traditional handcrafted techniques, the proposed IL-CNN model autonomously detects and encodes high-level features such as insect shape, texture, and boundary outlines. A Region Proposal Network is embedded within the architecture to identify potential insect locations within the image. Position-sensitive score maps are then generated to accurately localize and differentiate insect species even in visually cluttered grain environments. The extracted feature vectors are passed on to the classification and segmentation layers for further processing.

4.4 Model Training Engine

Training of the IL-CNN model is conducted using a labeled dataset containing insect species annotations and bounding masks. The system is trained through supervised learning using loss functions such as categorical cross-entropy, optimized with backpropagation. To prevent overfitting and ensure robustness across diverse storage conditions, the training process includes dropout regularization, learning rate scheduling, and real-time data augmentation such as image flipping and brightness adjustment. Performance is monitored throughout the training using validation accuracy, loss convergence curves, and mean Average Precision (mAP). Transfer learning with pretrained base models is incorporated to reduce training time and improve accuracy, especially given the limited size of domain-specific datasets.

4.5 Prediction and Inference Phase

Following successful training, the system enters the inference phase where it is used to process new, unseen images. The IL-CNN model predicts the presence and type of insects, highlights their exact location through segmentation masks, and calculates infestation severity based on count and density. The model also estimates the potential impact on grain quality by analyzing the spread and concentration of insects. Interpretability tools are integrated into the inference engine to visualize the regions that contributed to each prediction, offering transparency and confidence to the end-user. Low-confidence cases are flagged for manual review to minimize the risk of misclassification.

4.6 Deployment and Integration

The final component of the system involves deploying the application in real-world grain storage and monitoring environments. A web-based interface built with Flask, HTML, and Bootstrap enables users to interact with the system effortlessly. Admin users can upload datasets, initiate model retraining, and adjust insect classification parameters, while general users can submit images and receive instant analysis. The system can be integrated into existing warehouse IT systems or connected to IoT camera devices for continuous surveillance. It supports edge computing for offline environments and cloud deployment for scalability. To ensure operational security and user accountability, access control and data logging features are implemented, with future-proofing mechanisms such as continuous learning modules designed to adapt to evolving insect threats over time.

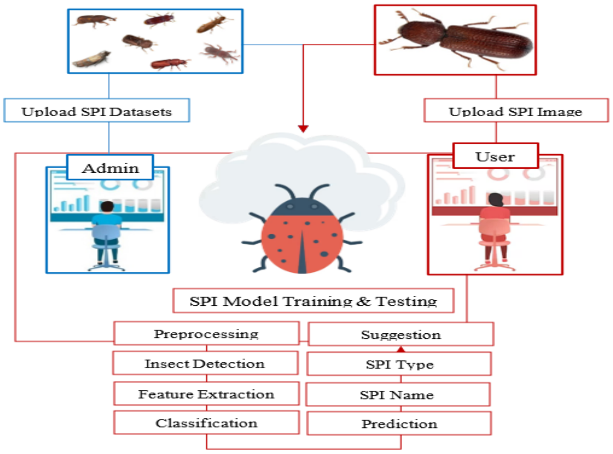

Fig 4.1 System Architecture

V. CONCLUSION

In conclusion, the design and development of a web-based detection and quantification system for stored product insects using Incremental Learning-CNN instance segmentation has the potential to provide an effective and efficient solution for identifying and measuring the extent of infestation in stored food products. By using advanced computer vision techniques to accurately detect and quantify insects in stored products, the system can help prevent economic losses, reduce the risk of contamination, and improve overall food safety. The proposed system offers several advantages, such as high accuracy in detecting and quantifying insects, reduced manual labor, and increased speed of processing. The use of IL-CNN instance segmentation allows the system to identify and count individual insects with a high degree of accuracy, even in images with complex backgrounds or varying levels of infestation. Additionally, it is a userfriendly system that can be easily accessed through a web-based interface, making it accessible to a wider range of users. Throughout the design and development process, careful consideration was given to usability, performance, security, and error handling, in order to ensure that the system was both reliable and user-friendly. Testing was performed at each stage of the development process, and a comprehensive testing plan was developed to cover a wide range of scenarios and ensure the system's reliability and accuracy. Overall, the design and development of a web-based detection and quantification system for stored product insects using IL-CNN instance segmentation has the potential to revolutionize the way that agricultural and food processing industries detect and prevent insect infestations. With further refinement and optimization, this system could become an essential tool for ensuring food safety and preventing economic losses due to insect infestations.

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