**Weed Detection and Segmentation in Corn**

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**Introduction**

Weed detection and segmentation in corn fields play a pivotal role in the advancement of precision agriculture. Traditional methods such as manual weeding or uniform herbicide spraying are labor-intensive, imprecise, and often result in environmental harm. Weeds directly compete with crops like corn for vital resources, leading to considerable reductions in yield. According to the Food and Agriculture Organization (FAO), weed infestation can result in a **30–70%** yield loss in maize, particularly in low-resource farming environments.

Modern agricultural technologies are turning toward deep learning-based visual systems to address these challenges. These systems enable high-resolution image analysis, allowing for accurate, pixel-level identification of weeds and crops. For example, autonomous robots or UAVs can perform real-time segmentation of corn fields and apply herbicide precisely to the affected regions, minimizing chemical use while improving crop health and productivity.

This transformation is supported by global market trends. The **agricultural robotics sector** is projected to grow to **USD 35 billion by 2030**, with precision weeding solutions such as autonomous sprayers and intelligent vision systems playing a key role (Allied Market Research, 2024). These technologies offer economic, environmental, and operational advantages that are driving adoption worldwide.

To train and evaluate our model, we utilize two primary datasets. The **DeepWeeds dataset** contains over **17,000 RGB images** of 8 weed species collected from Australian pastures under real field conditions, making it ideal for robust classification tasks. Additionally, the **SugarBeet2016 dataset** provides finely labeled semantic segmentation masks for weeds and crops (originally sugar beet), which we adapt to simulate corn-field conditions for model training and testing.

**References**

* Allied Market Research. (2024). *Agricultural Robots Market by Component, Type, Application, and End User: Global Opportunity Analysis and Industry Forecast, 2021–2030*.
* Food and Agriculture Organization of the United Nations. (FAO). *Weeds and their Impact on Crops*.
* Olsen, J., Aase, J. K., & Laursen, M. S. (2019). *DeepWeeds: A Multiclass Weed Species Image Dataset for Machine Learning*. <https://research.csiro.au/deepweeds/>
* Chebrolu, N., Lottes, P., & Stachniss, C. (2017). *SugarBeet2016: Dataset for Plant Classification and Segmentation in Precision Farming*.

**Literature Survey**

**1. A Keypoint-Based Method for Detecting Weed Growth Points in Corn Field Environments**  
Liu and Xu [1] proposed a novel deep learning approach based on **keypoint detection** to identify weed growth centers (e.g., shoot apices) in corn fields. Unlike traditional bounding box or segmentation methods, this technique allows for **precise targeting** of herbicides by focusing on central growth points of weed structures. The method shows high robustness in cluttered, real-world field environments where weeds often overlap with corn plants, enhancing precision for robotic weeding systems.

**Reference**  
[1] M. Liu and X. Xu, “A Keypoint-Based Method for Detecting Weed Growth Points in Corn Field Environments,” *Agriculture*, vol. 13, no. 1, pp. 1–14, 2023. DOI: [10.3390/agriculture13010091](https://doi.org/10.3390/agriculture13010091)

**2. Deep Learning for Weed Detection and Segmentation in Agricultural Crops Using Images Captured by an Unmanned Aerial Vehicle**  
Silva and Siqueira [2] utilized **U-Net** and other convolutional neural networks to perform weed segmentation on aerial images taken by UAVs. Their pipeline processes RGB and multispectral imagery and performs pixel-wise classification of crops and weeds. The study demonstrated that U-Net achieves high accuracy in varied field conditions, validating the UAV + deep learning combination as a scalable solution for **large-area weed monitoring**.

**Reference**  
[2] J. A. O. S. Silva and V. S. de Siqueira, “Deep Learning for Weed Detection and Segmentation in Agricultural Crops Using Images Captured by an Unmanned Aerial Vehicle,” *Remote Sensing*, vol. 13, no. 22, pp. 1–20, 2021. DOI: [10.3390/rs13224588](https://doi.org/10.3390/rs13224588)

**3. Analysis of the Application Efficiency of TensorFlow and PyTorch in Convolutional Neural Network**  
Novac and Chirodea [3] conducted a performance comparison between **TensorFlow** and **PyTorch** for CNN training and deployment. Their experiments showed that **PyTorch offers greater flexibility and debugging ease**, making it suitable for prototyping and research workflows, whereas TensorFlow performs better in **deployment scalability and model optimization**, which is crucial for agricultural AI applications in production settings.

**Reference**  
[3] O.-C. Novac and M. C. Chirodea, “Analysis of the Application Efficiency of TensorFlow and PyTorch in Convolutional Neural Network,” *Electronics*, vol. 11, no. 23, pp. 1–15, 2022. DOI: [10.3390/electronics11233953](https://doi.org/10.3390/electronics11233953)

**4. An Image is Worth 16x16 Words: Transformers for Image Recognition at Scale**

Authors: Alexey Dosovitskiy et al.

Published by: ICLR 2021

Summary:

This groundbreaking paper introduces the Vision Transformer (ViT) — a novel architecture that applies the Transformer model (originally developed for NLP) directly to sequences of image patches (16×16 pixels). It removes the need for convolutions and demonstrates that with sufficient data and compute, ViTs outperform traditional CNNs on image classification tasks. The paper highlights that Transformer models can match or exceed CNN performance when trained on large datasets like ImageNet-21k or JFT-300M.

**5. ImageNet Classification with Deep Convolutional Neural Networks**

Authors: Alex Krizhevsky, Ilya Sutskever, Geoffrey E. Hinton

Published by: NeurIPS 2012

Summary:

This landmark paper presents AlexNet, a deep convolutional neural network that achieved record-breaking performance on the ImageNet 2012 classification task. The architecture leverages ReLU activation, dropout, and GPU training to efficiently train a deep model with 60 million parameters. AlexNet significantly outperformed previous methods, effectively marking the revival of deep learning in computer vision.

**6. Review of Weed Detection Methods Based on Computer Vision**

Authors: Zhangnan Wu, Yajun Chen, Bo Zhao, Xiaobing Kang, Yuanyuan Ding

Published in: Sensors, 2021

Summary:

This paper provides a comprehensive review of weed detection techniques using computer vision, categorizing them into traditional image processing, machine learning, and deep learning methods. It emphasizes the shift toward deep learning approaches (e.g., CNNs, YOLO, and U-Net) due to their superior detection accuracy and adaptability in real-field scenarios. The paper also identifies challenges such as occlusion, illumination variation, and real-time processing requirements, and calls for more robust datasets and lightweight models.

Certainly! Here's the **integrated but separated** version of the literature survey with **short summaries and IEEE-style references**, organized **paper by paper**:

**7. Semantic Segmentation for Weed Detection in Corn**  
*Teng Liu, Xiaojun Jin, Kang Han, Feiyu He, Jinxu Wang, Xin Chen, Xiaotong Kong, and Jialin Yu*

Liu *et al.* [1] proposed an efficient weed detection strategy using **semantic segmentation** with the DeepLabV3+ model. Instead of explicitly labeling and detecting various weed species, their method focuses on segmenting corn plants only. Any green pixels outside the segmented corn areas are classified as weeds. This indirect labeling approach significantly simplifies training and improves generalization. To enhance real-time usability, they applied **knowledge distillation**, compressing the model into a lightweight version that retains high accuracy while enabling fast inference on mobile or embedded devices. The method achieved strong performance in field environments, suggesting practical applicability for deployment in agricultural robots or UAVs.

**Reference**  
[1] T. Liu, X. Jin, K. Han, F. He, J. Wang, X. Chen, X. Kong, and J. Yu, “Semantic Segmentation for Weed Detection in Corn,” *Biosystems Engineering*, vol. 230, pp. 82–96, 2023. DOI: [10.1016/j.biosystemseng.2023.02.003](https://doi.org/10.1016/j.biosystemseng.2023.02.003)

**8. Real-Time Weed Detection Using Computer Vision and Deep Learning**  
*Luiz Carlos M. Junior, José Alfredo C. Ulson*

Junior and Ulson [2] presented a **YOLOv5-based object detection system** for real-time identification of five glyphosate-resistant weed species. They created and released a custom annotated dataset, using **data augmentation** and **transfer learning** to enhance the robustness and convergence speed of the models. Among the tested models, YOLOv5m offered the best balance between performance (77% accuracy) and speed (26 FPS), proving effective on standard hardware. The authors emphasize the system’s potential for future deployment on **edge devices** such as Raspberry Pi, enabling scalable and low-cost smart weeding solutions.

**Reference**  
[2] L. C. M. Junior and J. A. C. Ulson, “Real Time Weed Detection using Computer Vision and Deep Learning,” *Journal of Intelligent & Robotic Systems*, vol. 106, pp. 1–15, 2022. DOI: [10.1007/s10846-022-01635-z](https://doi.org/10.1007/s10846-022-01635-z)

**9. Deep Learning-Based Segmentation of Multiple Species of Weeds and Corn Crop Using Synthetic and Real Image Datasets**  
*Artzai Picon, Miguel G. San-Emeterio, Arantza Bereciartua-Perez, Christian Klukas, Till Eggers, and Ramon Navarra-Mestre*

Picon *et al.* [3] developed a deep learning segmentation pipeline capable of identifying **multiple weed species and corn** at the pixel level. To reduce the cost of annotation, the authors constructed three datasets: real field images, synthetically generated composites from individual plant images, and weed-specific datasets. They employed an **improved PSPNet architecture** combined with an auxiliary classification head to enhance segmentation performance. Their best results (≈48% Dice Score Coefficient) were achieved using a hybrid of real and synthetic data. The model showed high consistency with expert annotations for broadleaf species, though performance declined with grass-like weeds due to visual similarities. This study supports the integration of synthetic data and multi-task learning for robust agricultural AI.

**Reference**  
[3] A. Picon, M. G. San-Emeterio, A. Bereciartua-Perez, C. Klukas, T. Eggers, and R. Navarra-Mestre, “Deep Learning-Based Segmentation of Multiple Species of Weeds and Corn Crop Using Synthetic and Real Image Datasets,” *Computers and Electronics in Agriculture*, vol. 188, p. 106353, 2021. DOI: [10.1016/j.compag.2021.106353](https://doi.org/10.1016/j.compag.2021.106353)

**Dataset Description**

**1. DeepWeeds Dataset**

The **DeepWeeds** dataset is a large-scale, real-world image dataset designed for weed species classification in natural agricultural environments. It was developed by CSIRO for the purpose of supporting automated weed detection across Australian pastures.

**Key Features:**

* **Total Images**: 17,509 RGB images
* **Weed Classes**: 8 common weed species including *Chinee apple*, *Lantana*, *Parkinsonia*, *Parthenium*, *Prickly acacia*, *Rubber vine*, *Siam weed*, and *Snake weed*
* **Non-weed Class**: A “negative” class with background or non-weed elements
* **Image Resolution**: 1,920 × 1,080 pixels (Full HD)
* **Camera**: Nikon D3200 DSLR used for consistent image quality
* **Environments**: Captured from 8 different field sites across Queensland, Australia
* **Annotations**: Each image is labeled with one of the 9 classes (8 weed + 1 background); bounding box annotations are not provided but can be inferred or added manually
* **Lighting Conditions**: Natural daylight with varying shadows, textures, and occlusion
* **Usage**: Excellent for weed species **classification tasks**, particularly for training CNN-based image classifiers in real-field conditions

**Download**: [Kaggle - DeepWeeds Dataset](https://www.kaggle.com/datasets/imsparsh/deepweeds)  
**Original Source**: [CSIRO DeepWeeds Project](https://research.csiro.au/deepweeds/)

**2. SugarBeet2016 Dataset**

The **SugarBeet2016** dataset is a benchmark dataset tailored for **semantic segmentation** in agricultural environments. It focuses on distinguishing between sugar beet crops and weeds in early growth stages using RGB imagery and pixel-level annotations.

**Key Features:**

* **Image Type**: High-resolution RGB images of sugar beet fields captured under controlled and real conditions
* **Segmentation Masks**: Each image is paired with a mask that labels every pixel as either:
  + **Crop (Sugar beet)**
  + **Weed**
  + **Background/Soil**
* **Multi-Class Semantic Segmentation**: Enables training of deep learning models such as U-Net, SegNet, or DeepLabV3+ for fine-grained plant classification
* **Frame Count**: Includes image sequences taken from the same location to capture growth and structural changes
* **Annotations**: Ground truth is provided in the form of binary and multi-class masks created through manual annotation
* **Lighting Variations**: Includes differences in sunlight and shadow to simulate real-world field conditions
* **Data Format**: Images and masks are provided as PNG files

**Download**: [Dataset Ninja - SugarBeets 2016](https://datasetninja.com/sugar-beets-2016)  
**Original Paper**: Chebrolu, N., Lottes, P., & Stachniss, C. “SugarBeets2016: Dataset for plant classification and segmentation in precision farming”