Ingenious Brain

Case Study

Breaking the Novelty Illusion:

How an Overlooked Cited Reference Unlocked **Novelty-breaking Prior Art**

Background

The client, an agritech company, approached us to check the novelty of a vehicle-mounted AI-driven plant treatment system designed to detect and treat plants. The system leverages advanced image segmentation techniques and is equipped with a camera module, plant treatment device, transformer-based unit, transformer-based encoder-decoder model, probability matrix generation, neural networking components, and other key gears.

Client's objective

The client required an invalidation search to identify prior art related to a novel image segmentation method for classifying plant and weed species. The method follows a specific process flow involving calculations in the encoding and decoding stages of the segmentation model. Their primary goal was to identify the exact prior art covering the segmentation method using transformer-based encoder-decoder architecture; the flow of processes within the encoding & decoding stages; and the probability matrix generation technique linked to selective plant treatment.

Our Strategic Approach

Our thorough search strategy involved an extensive exploration of the limited prior art within agriculture-focused AI systems. To ensure a comprehensive understanding, we broadened our scope to other industries employing similar segmentation methods.

Identifying a Relevant Non-Patent Literature (NPL)

- We located an NPL reference that the examiner also cited.
- This reference discussed an image segmentation method applicable to plants but was not explicitly linked to fertilizer application.
- The key focus was on segmentation alone, without integration into a plant treatment system.

Addressing the Probability Matrix Argument

- A narrow point raised by the applicant related to probability calculations.
- The prior reference did not explicitly mention probability mapping.
- However, since it discussed the SoftMax function, we argued that probability matrices could be derived from SoftMax outputs.
- The SoftMax function is a standard mathematical approach to convert a vector of values into a probability distribution, reinforcing our argument against the applicant's novelty claim.

Exploring Additional Reference on Multi-Species Treatment

- Another reference disclosed a plant treatment system based on species identification.
- This reference strengthened our case as it showed that multi-species treatment using AI segmentation is not novel.

Drafting Segmentation Maps with Multiple Objects

- We established that segmentation maps could be generated to include multiple objects, such as trees and other vegetation.
- This further supported our argument that plant detection signals are a standard extension of existing methods.

Snippets

8.	combining said decoded plant class-related vectors and decoded patch vectors to generate a plurality of class masks each defining a probability that a given patch corresponds to a given class,	**3.2. Decoder** The sequence of patch encodings $\mathbf{z_L} \in \mathbb{R}^{N \times D}$ is decoded to a segmentation map $\mathbf{s} \in \mathbb{R}^{H \times W \times K}$ where K is the number of classes. The decoder learns to map patch-level encodings coming from the encoder to patch-level class scores. Next these patch-level class scores are upsampled by bilinear interpolation to pixel-level scores. We describe in the following a linear decoder, which serves as a baseline, and our approach, a mask transformer, see Figure 2. **Linear.** A point-wise linear layer is applied to the patch encodings $\mathbf{z_L} \in \mathbb{R}^{N \times D}$ to produce patch-level class logits $\mathbf{z_{lin}} \in \mathbb{R}^{N \times K}$. The sequence is then reshaped into a 2D feature map $\mathbf{s_{lin}} \in \mathbb{R}^{H/P \times W/P \times K}$ and bilinearly upsampled to the original image size $\mathbf{s} \in \mathbb{R}^{H \times W \times K}$. A softmax is then applied on the class dimension to obtain the final segmentation map. **Mask Transformer.** For the transformer-based decoder, we introduce a set of K learnable class embeddings $\mathbf{cls} = [\mathrm{cls}_1, ..., \mathrm{cls}_K] \in \mathbb{R}^{K \times D}$ where K is the number of classes. Each class embedding is initialized randomly and assigned to a single semantic class. It will be used to generate the class mask. The class embeddings cls are processed jointly with patch encodings $\mathbf{z_L}$ by the decoder as depicted in Figure 2. The decoder is a transformer encoder composed of M layers. Our mask transformer generates K masks by computing the scalar product between L2-normalized patch embeddings $\mathbf{z'_M} \in \mathbb{R}^{N \times D}$ and class embeddings $\mathbf{c} \in \mathbb{R}^{K \times D}$ output by the decoder. The set of class masks is computed as follows $$\mathrm{Masks}(\mathbf{z'_M}, \mathbf{c}) = \mathbf{z'_M}\mathbf{c}^T \quad (4)$$ where $\mathrm{Masks}(\mathbf{z'_M}, \mathbf{c}) \in \mathbb{R}^{N \times K}$ is a set of patch sequence. Each mask sequence is then reshaped into a 2D mask to form $\mathbf{s_{mask}} \in \mathbb{R}^{H/P \times W/P \times K}$ and bilinearly upsampled to the original image size to obtain a feature map $\mathbf{s} \in \mathbb{R}^{H \times W \times K}$. A softmax is then applied on the class dimension followed by a layer norm to obtain pixel-wise class score forming the final segmentation map. The masks sequences are softly exclusive to each other i.e. $\sum_{k=1}^{K} s_{i,j,k} = 1$ for all $(i, j) \in H \times W$.	The decoder then translates these embeddings into segmentation maps using two variants: (1) a Linear Decoder, which applies a simple point-wise linear layer to generate patch-level class scores and then upsamples them to pixel-level predictions, and (2) a Mask Transformer Decoder, which introduces learnable class embeddings to generate class masks dynamically, improving segmentation accuracy. The mask transformer jointly processes patch embeddings and class embeddings, creating adaptive filters that enhance segmentation quality. Since the reference mentions SoftMax functions ; the softmax function is a mathematical function that converts a vector of numbers into a vector of probabilities, where the probabilities of each value are proportional to the relative scale of each value in the vector., we can infer that probability must be calculated for forming the final segmentation map.	Inferentially Supported

Our mask transformer is inspired by DETR [7], Max-DeepLab [52] and SOLO-v2 [55] which introduce object embeddings [7] to produce instance masks [52, 55]. However, unlike our method, MaxDeep-Lab uses an hybrid approach based on CNNs and transformers and splits the pixel and class embeddings into two streams because of computational constraints. Using a pure transformer architecture and leveraging patch level encodings, we propose a simple approach that processes the patch and class embeddings jointly during the decoding phase. Such approach allows to produce dynamical filters, changing with the input. While we address semantic segmentation in this work, our mask transformer can also be directly adapted to perform panoptic segmentation by replacing the class embeddings by object embeddings.

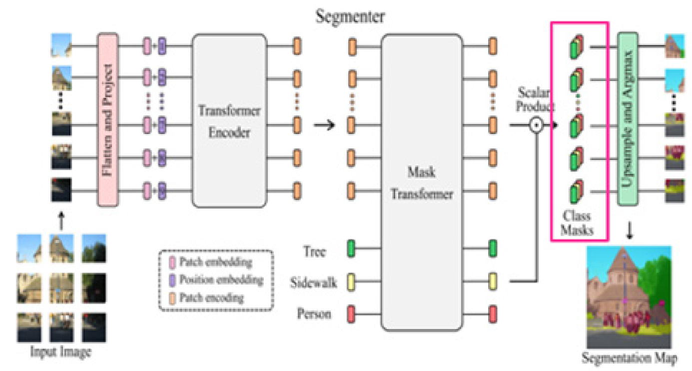

Figure 2: Overview of our approach Segmenter. (Left) Encoder: The image patches are projected to a sequence of embeddings and then encoded with a transformer. (Right) Decoder: A mask transformer takes as input the output of the encoder and class embeddings to predict segmentation masks. See text for details.

Conclusion

Through our invalidation search, we demonstrated that the transformer-based image segmentation method used in the plant treatment system was not entirely novel. Prior art references covered key elements, including:

- Image segmentation using encoder-decoder transformers.
- SoftMax-based probability mapping.
- Multi-species plant identification.
- Broad applications of segmentation beyond agriculture.

These findings provided a robust foundation to challenge the patent’s novelty and significantly bolstered our client's legal strategy. This case underscores the importance of expanding prior art searches beyond industry-specific constraints to identify broader technological overlaps.

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