Semiconductor Optoelectronics
ISSN: 1001-5868

WEED SEEDLING CLASSIFICATION USING AN IOT-ENABLED MODEL: A SMART AGRICULTURE APPLICATION

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ABSTRACT
"Smart agriculture" is an approach to farming that prioritizes constant observation and modification of agricultural practices to maintain food supply in the face of environmental change. It's indisputable that "smart farming" has the enormous effect that technology is having on agriculture. Smart farming's main focus is using technology to improve quality and efficiency in the agricultural sector. The Internet of Things (IoT) and digital image processing are two essential technologies in this field. The Internet of Things (IoT) includes multifunctional technology, and digital image processing paves the way for numerous IoT-integrated applications with its wide range of imaging sensors and methods. In this research, we investigate an analytical framework for integrating these technologies for weed identification in agriculture. To achieve this, we're introducing the Graph Weeds Net (GWN), an innovative graph-based deep learning model based on RGB images taken in complex environments and designed for recognising an extensive number of weed species. For exact weed identification, GWN captures different visual characteristics and produces multi-scale graph representations. Particularly useful for automated farming systems, GWN highlights important image areas to promote focused actions. Using a recently released benchmark dataset, we found that GWN performed highly, with a top-1 accuracy of 98.1%.
Keywords: Graph Weeds Net (GWN), Smart agriculture, Internet of Things

INTRODUCTION
Today, the number of devices connected via the Internet of Things (IOT) surpasses the global population [1]. IOT describes a world where various devices, from everyday gadgets to cars, connect to the internet and interact with other devices. This network primarily consists of sensors, wireless communications, and other technologies [1]. It's not just about electronic devices; everything from ATMs to alarm clocks falls under the IOT umbrella. This connectivity fosters a deeper interaction between humans and their environment, enhancing efficiency, reliability, and adaptability [2].

Image Processing

Humans depend significantly on visual input as their major source of information, with a

significant amount of our brain dedicated to processing what we see [3]. Image processing entails improving or analyzing images in order to gain insights [3]. This technology has advanced quickly and is now used in a variety of applications such as gesture recognition, driverless vehicles, medical imaging, and more [4].

Smart Agriculture:"Smart agriculture" refers to a modern approach to farming that uses technology to improve crop health and yield [5]. It's not only about employing technology; it's about monitoring crops, soil, and the environment in real time. While smart agriculture used to be primarily reliant on information technology infrastructure, tools such as mobile apps, sensors, cloud computing, and drones have made it available to farms of all sizes [6, 7]. IoT plays a critical role in this, improving agricultural operations ranging from crop monitoring to water management. It enables farmers to respond quickly to changes, ensuring ideal crop conditions [8,9]. Furthermore, IOT simplifies the agricultural supply chain, providing efficient logistics.

Drones, sensors, and IoT devices collaborate in the field of smart agriculture to provide farmers with important data for efficient farm management. With developments in imaging techniques such as thermal and hyper-spectral imaging, digital image processing, in particular, has demonstrated its efficacy in smart farming applications [11]. Farmers may receive professional advise quickly thanks to the integration of wireless networks and image processing, which aids in tasks such as crop management, weed detection, and plant health monitoring [12].

While both IOT and image processing have been used in numerous sectors, their combined use in agriculture is still relatively unknown. However, combining these two can result in improved outcomes in smart agriculture [13,14]. A important study named "Implementation of IoT and Image Processing in Smart Agriculture" revealed the potential of this combination, allowing ways of finding factors affecting plant growth [15].

2. METHODS

A weed is a plant that is growing in a wrong place. Smart agriculture depends significantly on plant management. The objective of weed plant management, which is part of the botanical aspect of pest management, is to stop weeds, especially harmful weeds, from interfering with desirable flora and fauna, such as domesticated plants and livestock, and to stop non-native species from becoming more numerous in natural settings than native species. Herbicides can be used chemically, hoes can be used manually or mechanically, mulch and soil solarization can be used to suffocate weeds, and extreme heat and fire can kill them [16]. However, knowing what kind of weed plant you're up against is essential before using any herbicides [17]. In this section, we will go through the basics of how to put up a smart agricultural application for classifying weed plants. The method of detecting weed plant seedlings using cloud-based IoT and image analytics is depicted in Figure 1. In this configuration, the IoT gadget uploads the photo of the cannabis plant to the cloud over a wireless network. When the cloud-based picture analysis are complete, the farmer is notified.

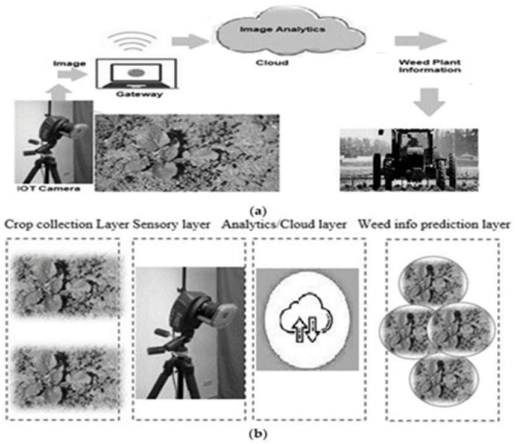

Figure. (a): A typical IOT-based image analytics model for smart agriculture [13]. (b): IOT-enabled smart agriculture architecture including crop collection, sensory, analytical/cloud, and prediction layers.

An Internet of Things (IoT)-enabled smart capture system and crop sensory system are displayed integrated in Figure 1. The graphic depicts the basic structure of the suggested approach. Layered architecture, with the analytics component deployed to the cloud, is also shown. Here we detail the specific processes taking place within the IoT-enabled framework.

Artificial Intelligence (AI)

Artificial intelligence (AI) is a subfield of computer science that tries to provide machines human-like intelligence and performance. The abilities of learning, reasoning, problem solving, perception, and understanding a language [18,19] all play a part in this.

Machine Learning (ML)

Learning plays a crucial role in AI. This concept, when applied to machines, describes their capacity for learning and growth over time. This is investigated in machine learning, which uses many kinds of methods to create models from existing data.

Deep Learning (DL)

Deep learning is an advanced branch of machine learning that employs artificial neural networks with multiple layers, often referred to as "deep neural networks" [20-29]. This depth, characterized by the number of layers in the network, allows for complex pattern recognition and data abstraction.

In applications like autonomous vehicles, deep learning models can identify and classify objects in real-time, such as distinguishing between a stop sign and a pedestrian. The efficacy of these models is contingent upon the architecture of the neural network and the availability of vast labeled datasets for training.

There are several architectures within deep neural networks:

Multi-layer Perceptron (MLP): A foundational network structure with multiple layers of nodes in a feed forward configuration.

Convolution Neural Network (CNN): Optimized for processing grid-like data, such as

images, by using convolution layers to filter input data.

Recurrent Neural Network (RNN): Designed for sequential data processing by incorporating loops to allow information persistence.

These sophisticated neural network architectures are at the forefront of technological advancements, driving innovations in various domains [30,31].

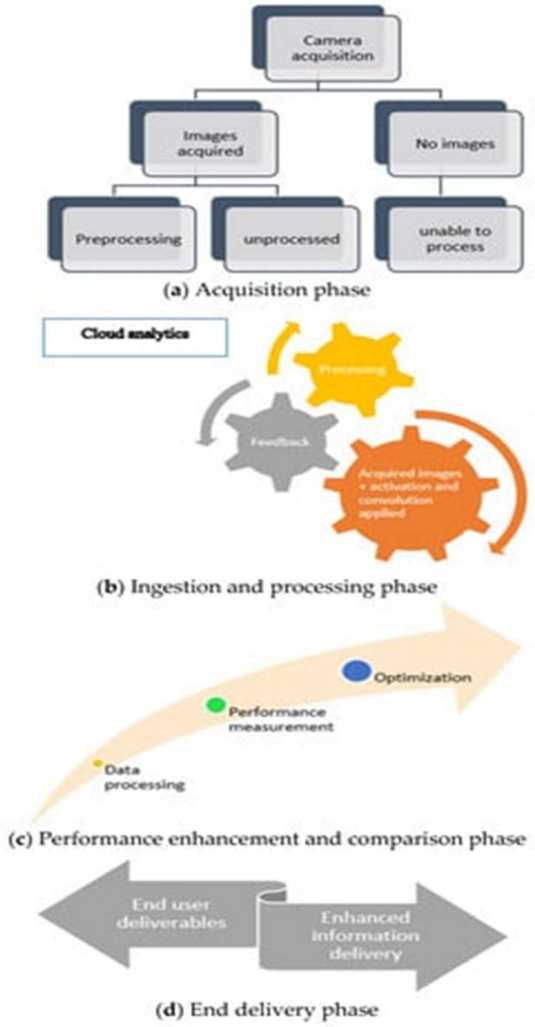

Figure 2. Flow graph of the entire system.

GWN ArchitectureOverview forWeed Classification

The Graph Weeds Net (GWN) is a sophisticated architecture tailored for the precise classification of weeds. Its foundation is built upon a unique local-global scheme, ensuring that the intricate details and broader aspects of weeds are both captured and represented accurately. The first component of the GWN is the Multi-scale Graph Convolution Layer. This layer is pivotal for processing the input RGB images. By operating across multiple scope scales, it ensures a comprehensive interpretation of the images. Whether it's the minute details or the overarching features of the weeds, this layer captures it all. As a result, each scale produces a distinct graph representation, encapsulating the spatial relationships and unique features of the

weeds.

Following this is the Graph Pooling Layer. Its primary role is to refine the data extracted from the images. By acting on the vertices of each graph, it employs a strategic selection mechanism. This mechanism focuses on specific patterns within the image, particularly those with a high likelihood of representing the target weed. In doing so, it emphasizes the most relevant information, filtering out any noise or unrelated details.

Lastly, the architecture incorporates a Recurrent Neural Network (RNN) Layer. This layer is tasked with consolidating the data from the multi-scale graph representations. By processing this data in a sequence, the RNN ensures that the system retains and utilizes previous information, leading to a holistic understanding of the weed's features. Ultimately, based on this comprehensive analysis, the layer delivers predictions, determining the precise classification of the weed.

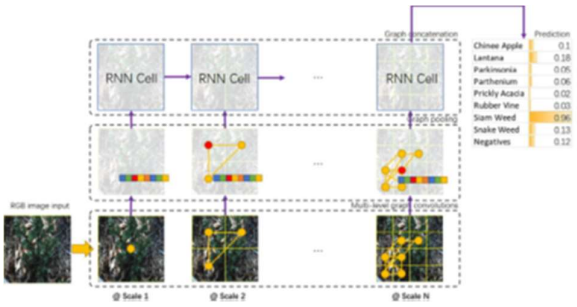

Figure 3: Graph Weeds Net (GWN)

2.1. Multi-scale weed graphs

Input: RGB Image $X \in R^{m \times n}$

Output: Weed species classification response y

Steps:

1. **Initialization:**
   a. Set scales $s=\{1,2,3\}$ representing global, 2x2, and 4x4 grid patches.
   b. Load pre-trained CNN model.
2. **Patch Extraction:**
   a. For each scale s in s:
      i. Extract patches from image X.
      ii. Store patches in set $s=\{v|i=1\ldots n\}$.
3. **Feature Extraction:**
   a. For each patch p in set s:
      i. Apply pre-trained CNN to patch p.
      ii. Obtain feature vector $v^s_p \in RDs$, where Ds is the dimension.
4. **Graph Construction:**
   a. For each scale s:
      i. Construct a directed graph $Gs=(\_s,As)$.

ii. Treat s as a set of vertex features.
iii. Define $As=aijs \in R^{ns \times ns}$ as a weighted adjacency matrix to represent relations among vertices.

5. **Weed Species Classification:**
   a. Associate a response y with the image and its multi-scale graphs Gs to indicate the weed species.
   b. For each patch p in Gs:
      i. Define y_p^s as a one-hot encoding vector indicating the presence or absence of the target weed species.
6. **Training Considerations:**

   a. Use only the image-level response y for supervision.
   b. Note: Patch-level annotations y_p^s and As are not required during training.
   c. The method operates as a semi-supervised learning approach.

2.2. Graph convolution layer

Input: Graph instances with arbitrary structures, Vertex features v_i^s and v_j^s

Output: Characterized weed patterns

Steps:

Initialization:
Estimate adjacency matrix A_s
within GWN.
Set $g(\cdot)$ as a linear function.
Estimate Adjacency Matrix *As*:
For each element a_{ij}^s in A_s:
Compute using the relation between vertices i and j.
Use Eq.(1) with bilinear pooling operations.
Decompose Ms using low rank decomposition.
Normalize Adjacency Matrix:
For each row A_i^s in $A_{s:}$
Normalize using the l2 norm of A_i^s
Compute Graph Convolutions:
For each layer l:
Compute the output $H_{\{i+1)}^s$ using $W_l^s A_{s,}$ and H_l^s

Introduce non-linearity using f_l^s

Pattern Exchange Among Vertices:
Multiply weighted adjacency matrix $A_s$with H_l^s
Interpret as pattern exchanging based on edge weights in A_s.
Determine Vertex Connectivity:
For each row $A_i^s$of As:
Determine weights of edges connecting $v_i^s$and a_{ij}^s
Transfer patterns from v_j^s to v_i^s based on a_{ij}^s value.
Compute Final Output:
Multiply A_sH_s with W_l^sTreat as computing D_s independent samples using a fully connected layer.

2.3. Vertex-wise dense layer

In general, stacking multiple graph convolution layers produces representations of weeds that are properly exact for the identification of weed patterns. As the adjacency matrix As can be learned during the computation of graph convolutions, it significantly raises model complexity and introduces the possibility of overfitting. In this study, these problems were mitigated by employing the vertex-wise dense layer, which computes independently on each vertex while sharing weights. By employing the adjacency matrix, there is no exchange of patterns between the vertices, unlike in graph convolution layers. The computations of a vertex-wise dense layer can be expressed as follows: $\boldsymbol{H}_{l+1}^s = f_l^s(\boldsymbol{H}_l^s \boldsymbol{W}_l^s),$

$W_l^s \in R^{p_l^s * p_{l+1}^s}$ is a matrix of a linear transformation: $R^{p_l^s} \rightarrow R^{p_{l+1}^s}$and fls introduces the non-linearity, where $\boldsymbol{Hs} \in R^{Dsxpls}$is the output of the l-th layer. The layer is a particular instance of the graph convolution layer if the adjacency matrix $\boldsymbol{As} = \boldsymbol{I}$. remains constant. This means that the vertex-wise dense layer can handle input graphs with any number of vertices.

2.4. Multi-scale graph pooling & concatenation

The complete graph weed representation at scale s, including the graph convolution layers and vertex-wise dense layers, is denoted as $\boldsymbol{Hsl} \in R^{Dsxpls}$It is easy to see how the number of vertices, denoted by Ds, and the size of their features, indicated by s, change at different zoom levels. Therefore, in this research, a two-stage pooling method was developed to aggregate the patterns from each scale.
To build complete weed representations, an RNN is first applied to the graphs, after which the vertices are pooled for each scale**.**

With the graph convolution layers and the vertex-wise dense layers, denote as the final graph weed representation at scale s.Notice that the vertex count *Ds* and the dimensions of the vertex featuresvary with the different scale s. Hence, to combine the patterns from each scale, a two-step pooling manner is devised in this study.

$$\boldsymbol{H}_L^s = (h_{L,ij}^s),\ i = 1,\ \ldots, D^s,\ j = 1,\ \ldots, p_L^s,$$

It can be done to apply the vertex-based pooling operations. The average pooling, for instance,

is seen in Eq..

$$\widetilde{\boldsymbol{H}}^{s}=\left(\frac{1}{D^{s}}\sum_{i}h_{L,i1}^{s},\frac{1}{D^{s}}\sum_{i}h_{L,i2}^{s},\ldots,\frac{1}{D^{s}}\sum_{i}h_{L,ip_{L}^{s}}^{s}\right)^{T}.$$

The different dimensions of the pooled graph representations are then corrected by a linear transformation.

$$\boldsymbol{H}^{s}=\boldsymbol{W}^{s}\widetilde{\boldsymbol{H}}^{s}.$$

The mapping from the pooled graph representation of scales to the consistent dimension p is given $W_l^s \in R^{p_l^s * p_l^s}$ As a result, we can represent a set of graphs using the notation $\{\boldsymbol{Hs}\}$. RNNs are used to process the sequential linput $\{\boldsymbol{Hs}\}$ in order to extract the global-local graph patterns from the series. As a result of the gradient vanishing and exploding problems that plagued earlier attempts at sequential modeling (Hochreiterand Schmidhuber, 1997; Cho et al., 2014), newer proposals have included gated methods (such as LSTM and GRU) that have proven highly effective. Using Hs as an input sequence, the hidden state $\{\boldsymbol{Hs}\}$. can be calculated using the corresponding Eqs.

$$\mathbf{i}^{s}:=\sigma(\mathbf{W}_{xi}\mathbf{H}^{s}+\mathbf{W}_{hi}\mathbf{h}^{s-1}+b_{i}),$$

$$\mathbf{f}^{s}:=\sigma(\mathbf{W}_{xf}\mathbf{H}^{s}+\mathbf{W}_{hf}\mathbf{h}^{s-1}+b_{f}),$$

$$\mathbf{o}^{s}:=\sigma(\mathbf{W}_{xo}\mathbf{H}^{s}+\mathbf{W}_{ho}\mathbf{h}^{s-1}+b_{o}),$$

$$\dot{\mathbf{c}}^{s}:=tanh(\mathbf{W}_{xc}\mathbf{H}^{s}+\mathbf{W}_{hc}\mathbf{h}^{s-1}+b_{c}),$$

$$\mathbf{h}^{s}:=\mathbf{o}^{s}\odot tanh(\mathbf{c}^{s}).$$

Where**i***s*, **f***s* and **o***s* is the input gate, forget gate and output gate, respectively. Such gated mechanism controls the extent of the patterns are introduced or kept when computing the cell state **c***s* and hidden state**h***s*.

2.5. Weed identification

For weed detection using dense layer, we use the state of the final RNN cell. In particular, the dimension is provided by the linear layer as the number of desired weed types, and the weed probability vector is created via application of a sigmoid function. It is important to note that the sigmoid function is utilized in place of the softmax function, which is employed for mutual exclusion classification issues, when a single input image contains different weed kinds concurrently. To further facilitate optimization, we adopt an average of multiple binary entropy loss functions, one for each class. Supervision information was annotated at the picture level, but not the patch level, and the outputs of the proposed method offer prediction at the image level. The vertex-level patterns of Eq. (6), for instance, are computed under the guidance of the image-level labels alone, despite the fact that they are supposed to include correct localized patterns. Since the pooling method summarizes patch patterns, the weeds may be most strongly

linked to the patches that contribute most heavily to the summary. As a result, we engage in patch-level semi-supervised learning.

2.6. Image Data Set

The present research makes use of a freely accessible image dataset that includes images of weeds, total approximately 4234 individual plants and representing 12 weed plant species [26]. These 12 species of weed plants were gathered by the Signal Processing Club at Aarhus University. Images of representative weeds from each group are displayed in Figure.

Figure. Weed plant image dataset samples.

Color image processing in the HSV space is used to segment all of the weed images, and then morphological procedures are performed on the segments. Figure displays some example segmented photos of weeds.

Figure 4. Segmented weed plant image dataset samples.

3. CONCLUSION

In this paper, we introduce Graph Weeds Net, a unique deep architecture that uses RGB images gathered from rangelands to precisely recognize weed species. GWN is designed to incorporate

weed-related knowledge by portraying an RGB image as multi-scale graphs.Vertex-wise dense layers, multi-level graph pooling methods, and graph convolution layers are all components of the GWN architecture, which can build fine-grained level deep representation and is projected to enhance the performance of weed detection tasks. Additionally, GWN has the option to pinpoint the main areas of the full image, indicating the high likelihood of the target weeds being present rather than the foreground or other plants. The important thing to note is that no prior knowledge of weed localisation through annotation is necessary, making GWN a semi-supervised learning strategy that reduces the laborious annotation responsibilities. GWN is assessed using a freshly released benchmark dataset called Deep Weeds, and it performs at the cutting edge, with a top-1 accuracy of 98.1%. Future work will concentrate on enhancing the efficiency of the architecture while enhancing the performance of the identification task.

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