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Hybrid between Ontology and Quantum Particle Swarm Optimization for Segmenting Noisy Plant Disease Image

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Abstract: One of the main risks to food security is the plant diseases, but because of the absence of needed infrastructure and actual noise, scientists are faced with a difficult in detection plant diseases in the real image without de-noisy process. The proposed solution in this paper is based on Ontology to support semantic segmentation. Where, the semantic segmentation divides images into non-overlapped regions, with specified semantic labels allocated. The QPSO (quantum particle swarm optimization) algorithm has been used in segmentation of an original noisy image. The proposed method outperforms state-of-the-art algorithms in terms of global accuracy. The proposed method achieves 88% which is superior to other approaches, likely because of the consistency of the semantic implementation, weighting of features and the implementation of data and knowledge required. Our results show that a classification based on the proposed method is better than the state-of-the-art algorithms. The proposed method is evaluated, with 49,563 images from healthy and diseased plant leaves, 12 plant species were identified and 22 diseases. The classification accuracy of the proposed method is 86.2%, showing that the strategy is appropriate. We enhanced PDO (Plant Disease Ontology) to be EPDO (Enhance Plant Disease Ontology). The segmented noisy image elements are paired with EPDO with derived features that come from QPSO. The proposed method also saves time of de-noisy process and effort for removing the noise at a noise level from the input image σ =70.

Keywords: Image segmentation, Ontology, Quantum particle swarm optimization algorithm.

1. Introduction

Several actors, such as plant diseases, weather change and others, are threatening food security. Plant diseases threaten world food safety and farmers who rely on safe plants to livelihood. More than 80 percent of agricultural manufacturing is produced by smallholder farmers. The reduction in output of more than 50% [1] was caused by diseases and pests. Moreover in small farm homes, more than 50 percent of starving individuals reside. Smallholders farmers especially susceptible to pathogenic food production disruptions.

Researchers are trying differently to avoid plant reduction caused by pests and diseases. In this paper we show the strategy by means of an Ontology using a total of 49,563 noisy images (noisy level $\sigma = 30$) produced publicly accessible by the PlantVillage project [2] for a total of 12 plant types of 22 illnesses (or good ones).

The last few years have seen great advancement in computer vision as well as image recognition. To determine the classifier of images for plant disease treatment, we need a big checked dataset of injured and good plants. There really is no dataset and smaller datasets are not accessible openly. To fix this issue, we have been using the PlantVillage project which includes ten of thousands of images of good and diseased crops that are publicly and readily accessible. We used 49.563 noisy photos in this paper

to categorize 12 plant types that are 22 safe or injured. The efficiency of the method proposed is evaluated on the basis of the capacity of 34 possible classes to identify right crop diseases.

For higher-level regional-based feature description, non-supervised segmentation algorithms like mean shift [3], SLIC superpixel [4], graph-based segmentation [5, 6], JSEG [7], and TurboPixel [8] were used. These unsupervised segmentation methods prefer to cover segment items with high inner contours heterogeneous parts. The segmented areas lose sementic meaning due to semantic consistency.

The objective of this paper is together the image segmentation, object detection, and semantic solutions to identify the diseases of plants. The method suggested is distinct from the previous methods in which the segmentation integration was postponed in the close-end phase, while the proposed method applied the segmentation integration in beginning.

Notable features can be found in other apps such as image retrieval or pattern recognition and other areas such as biomedical and geospatial picture analyses, which include the proposed method and ontological inference. Additionally, an ontology constructed from the images in a specific database can be used to infer item labels within the same domain of concern in another / other database(s). However, since each ontology contains the knowledge of certain domain, it can't be used in another domain effectively. That means it is somewhat difficult to reuse an extremely specific domain ontology in other domains. The primary advantage of the suggested ontology deduction is that it can deal with various kinds of relationships at distinct rates of neighborhood and abstraction levels, which makes it relevant to other apps. The proposed method EPDO that will provide agronomists and farmers with solutions for crop disease detection and the collection of epidemiologic statistics, to integrate information associated to both plant disease as well as plant physiology, to help interpret phenotypic plant pathogens and disease procedures in attempt to influence integrated information of both fields.

The rest of this paper is organized accordingly. The related work is displayed in section 2. Section 3 presents the Enhanced Plant Disease Ontology (EPDO). Section 4 explains the suggested method. Section 5 presents the results of the test. In section 6, conclusion of this work is presented.

2. Related works

Applicability of knowledge relying on image analysis for plant diseases [9-13] has been shown by several research. But the formalized methodology to make advanced information reusable is lacking. Many variables, including air pollution and low-temperature and stressors including pests or pathogens, can cause crop diseases primarily. Infectious plant diseases are produced by the pathogens such as bacteria, viruses and insects.

The plant diseases are the main risks to the food security. We are constructing a plant disease enhancement (EPDO) for the PDO [14, 15] as guide for crop disease as portion of a major project to create Ontologies that recognize both plant type and disease. We have created EPDO that will provide agronomists and farmers with solutions for crop disease detection and the collection of epidemiologic statistics, to integrate information associated to both plant disease as well as plant physiology, to help interpret phenotypic plant pathogens and disease procedures in attempt to influence integrated information of both fields. There are many methods that applied to detect the plant diseases, but when an input plant image is noisy, the efficiency of this methods is decreased. With 49,563 images from healthy and diseased noisy plant images, 12 plant species were identified and 22 diseases are identified using the proposed method. Also, if the noisy level of the input image equal to 70 (σ=70), the proposed method can detect the plant diseases. So, the proposed method does not need to remove the noise from the input image. This is means that the proposed method saves the time and efforts for removing the noise at noise level from the input image σ=70. The suggested EPDO technique to provide landowners with alternatives for the identification of crop diseases and the compilation of epidemiological statistics, to incorporate both plant disease and plant physiological data, to assist understand phenotypic plant pathogens and disease processes to affect the embedded data in both areas. The major benefit of the proposed ontology deduction, which leaves it important to other applications, is that it covers multiple kind of relations at different stages of neighborhood and abstraction.

The Infectious Disease Ontology plant (IDOPlant) [16] developed. IDOPlant interoperated with both the Foundry of Open Biomedical Ontologies (OBO) partners and candidates, for example the Gene Ontology (GO), the Plant Trait Ontology (TO), and the Plant Ontology (PO). Some ontologies used to define plant diseases have been described in Table 1.

Table 1. Indicates some external ontologies for the description of plant diseases

ID	Ontology Name	Domain
TO [17]	Trait Ontology	Features of plants
GO [18]	Gene Ontology	Biological, molecular as well as sub-cellular mechanisms elements
PO [19]	Plant Ontology	Plant constructions and phases of progression
ENVO [20]	Environment Ontology	Features of the environment and residents
CHEBI [21]	Chemical Entities of Biological Interest	Entities Chemical
PATO [22]	Phenotypic Quality Ontology	Phenotypic features
NCBItaxon [23]	NCBI Taxonomy Classification	Taxonomic living organism classification
GAZ [24]	Gazetteer	Geographical data

The GO, which has been developed as part of the PAMGO project [25], is connected to the IDOPlant *multi-organism*. The IDOPlant has been developed to cover many infectious diseases of plants. There are different extensions to the IDOPlant and existing IDO. Due to the current IDO extensions, particular diseases like malaria and Brucellosis impact human and animal life [26] are concentrated in particular.

The first step in [27, 28] was presented by the Plant-Pathogen Interactions Ontology (PPIO), which is the axiomation of plant-pathogen interactions. The Pseudomonas syringae pv. Tomato (PsPto) has been used to improve PPIO, where the first simulation issue is PsPto disease due to the general understanding of this pathogenic method. PPIO created on PO, TO Ontology, axioms and Pathogenic Effects phrases.

The disadvantage of these Ontologies is that of using a negation that needs the use of an expressive fragment of OWL which cannot be guaranteed by polynomial time, automatically generated reasoning. Therefore, such axioms are not yet extensively used in phenotype Ontologies. There are also considerable disadvantages to the PATO strategy. To generate a term on the fly, curators need to look at several ontologies and this strategy generates words and sentences that are sometimes stilted or not frequently used in literature and workshop environments. The absence of phenotype data mixed with species neutral Ontological conditions and the need for norms for the creation of EQ declarations to define plant phenotypes are two significant constraints to implementing a comparable strategy in plants. However, the following two major current funds are accessible to encourage post-composed Ontological analysis of plant phenotype data: (1) excellently-developed ontologies for the plant sciences, especially plant ontology (PO), [19] and Gene Ontology (GO) [18]; 2) curated collections of mutant phenotype illustrations in model organisms and crop databases for various plant species. Besides GO, several kinds of science information under the name ontology have become structural. While the categories of traditional forms, definitions and logic have constraints, ontology is more flexible. Instead of showing a particular approach to ontology, it might be more useful for biologists.

In [29] PSO Quantum Theory and QPSO algorithms proposed. As the particle can exist in QPSO throughout all generations, this enhances the variety of the population. QPSO has a strong search capacity globally. The QPSO control is greater than PSO algorithm, where it has one parameter. In terms of the search capacity, QPSO is the updated and expanded version of the PSO algorithm as well as its accuracy. QPSO algorithm particles may pop up in every search space, which focuses on the delta potential. The QPSO algorithm may skip fault the standard PSO algorithm, but it cannot ensure global convergence with probability 1. The positions and speeds of the particles in quantum space can never be evaluated concurrently. In [30] the QPSO is introduced to save running time and overcome dimensionality using the cooperative technique (CQPSO). In [31] a combination of the PSO algorithm with the growing seed region (SRG) introduced. The SRG technique performs seed segmentation of the image. The PSO algorithm is used for measuring the requirements of similarity and the average region. QPSO method [32] used to encode the present location of the particle, search particles and carry out mutations, alternately, with quantum bits, quantum rotation gate and quantum not gate.

Several segmenting techniques [3-8] are available, and it is difficult for scientists to discover an effective technique of image segmentation. Several techniques formulate object detection in order to locate notable objects in the foreground of the image, while semantic image segmentation defines each pixel with a predetermined label. Semantic image segmentation, image segmentation, and object detection seem to be three heterogeneous issues, since pixel labels profit from the segmentation and the separation of the object detector in semantic segmentation. Semantic segmentation of images combines the hardness of segmentation and object detection with the complex.

These issues have been checked by different literature techniques in any situation of their dependence. This paper presents the technique for semantic image segmentation, considering and developing image segmentation and object detection at the same time. In particular, images are divided into regular items.

3. Enhance plant diseases ontology (EPDO)

Ontology represents formally and explicitly a conceptualization for sharing [33]. The *conceptualization* is now a model of the world phenomenon by ideas in the summary of this concept; Ontology means sharing a consensual knowledge, agreed upon by experts, the concept types and limitations for their use are represented *explicitly*, and the Ontology should be machine-readable by means of *formality*. Ontology defines the ideas of semantics and their links. In this paper the Web Ontology Language (OWL) is employed for ontological formalism as a knowledge representation language. Where the OWL is one of the most popular ontology languages.

The next stages in the development of EPDO are proposed:

1. Detect the Ontology domain as well as the scope.
2. Consider reuse of Ontologies that exist. We looked for the corresponding Ontology in order to identify a plant domain.
3. Calculates significant terms in Ontology. The terms are applied to define the concepts and relationships that defines the domain area.
4. Describes the hierarchy of class and classes.
5. Set the class characteristics. Fig. 1 shows the characteristics of the data type.

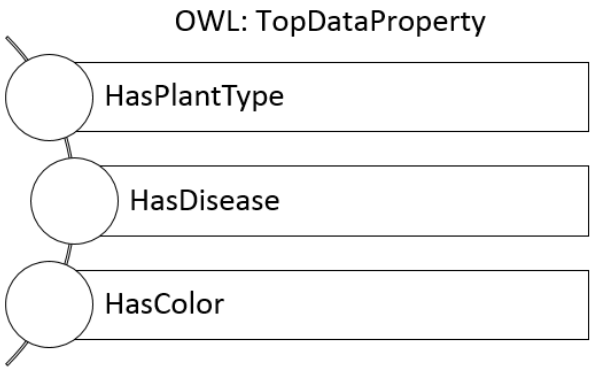

Figure. 1 Properties of data type to display the attributes extracted

6. Directly define the class-related constraints. Restrictions like domain and concepts must be defined. For illustration, the value of the *hasDisease* property is limited to the integer of data type.
7. Create instances. The segmentation and feature extraction module create these instances.

The PO is applied to enhance the PDO [19]. The PDO includes plant disease-specific terms and corresponding conditions imported from other ontologies, like OBI organisms; disease disorders and disease course from OGMs; ENVO habitat; GO (gene ontology) reproductive complex, and hosting (GO) reproductive complex [18]; the NCBItaxon bacterium and virus [23].

Then, EPDO has created new classes, axioms, individuals, rules, and terms for the integration of the PDO. These modifications identify the leaves of plants and their diseases. Where, we added features of plant diseases, color, and various type of plant in classes and sub-classes such as 'plant disease', 'color' and 'type' sub-classes. The OWL Class Hierarchy of EPDO is presented in Fig. 2.

The EPDO varies from current PDO because the PDO concentrates on particular plant affected diseases or pathogens. By fact, 12 species of plant and 22 infectious diseases are covered by the EPDO. Additionally, as portion of the Plant Phenotype Ontology Project, the EPDO is being improved, which involves all plant stress and is not restricted to infectious diseases. Our method calls for multiple plans covering the construction of fresh terms and the importation of terms and the creation of connections with other ontologies.

3.1 Modularisation of ontology

PDO is a research of pathogens (infectious organisms) and environmental (physiological) diseases of plants. Organisms like (fungi, omycetes, bacteria, viruses, and viroid), and virus like (organisms, phytoplasmas, protozoa, nematodes and parasitic plants) are all cause infectious disease. Ectoparasites including insects, mites, spinal cells or any other pests that influence the health of plants by eating plant tissues are not identified Plant pathology often includes the research on detection of pathogen, etiology of diseases, disease cycles, financial impacts, epidemiology of plant diseases, plant resistance, how plant diseases influence people and animals, path system genetics and treatment of plant diseases [14].

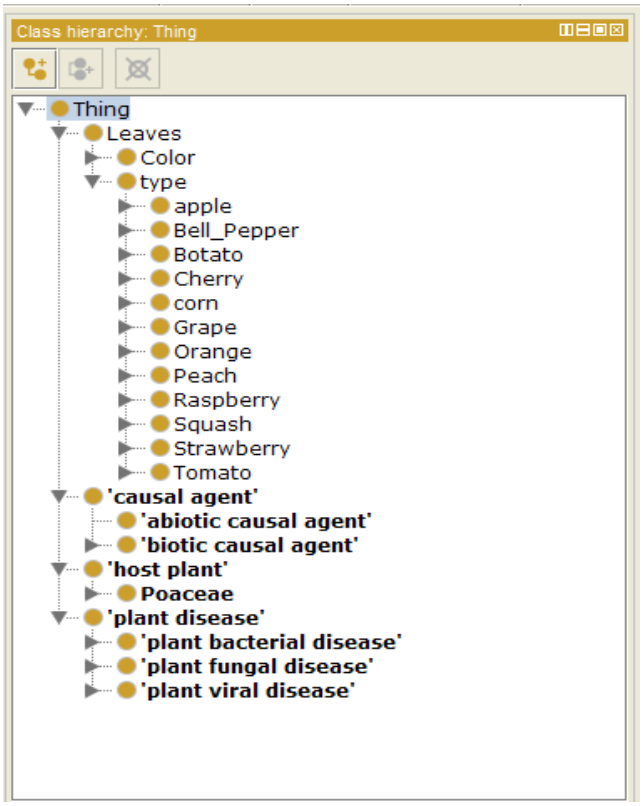

Figure. 2 The OWL class hierarchy of EPDO

This paper includes two components, one domain and one feature, for modularization of EPDO. The Ontology can be transferred through the modularization and skip the reuse of a whole domain of Ontology if only a part is necessary only. Relationships and appropriate concepts are only used for the modularization of Ontology in the Ontology modelling.

- **Ontology Domain**

The EPDO Ontology domain shows the entities which discovered the domain. In the domain Ontology, the relationship between the classes and their sub-classes are described as subset notation (⊑) as the following. For instance, the relationship (1) shows Leafs, causal agent, plant disease, host plant are the subsets of Thing. Similarly, relationships (2) describes oryza, triticum, hordeum, zea are the subsets of poaceae. Also, relationships (3) describes abioti viral disease, abiotic causal agent are the subsets of causal agent. Relationships (4) describes plant bacterial disease, plant fungal disease, plant viral disease are the subsets of causal agent.

$$Leafs, causal\ agent, plant\ disease, host\ plant \sqsubseteq Thing \quad (1)$$

$$oryza, triticum, hordeum, zea \sqsubseteq poaceae \quad (2)$$

$$abioti\ viral\ disease, abiotic\ causal\ agent \sqsubseteq causal\ agent \quad (3)$$

$$plant\ bacterial\ disease, plant\ fungal\ disease,$$

$$plant\ viral\ disease \sqsubseteq causal\ agent \quad (4)$$

- **Ontology Features**

Feature ontology describes ideas that outline the features of various attributes during the feature extraction process. EPDO Ontology features provide the features of various characteristics identified during the feature extraction. Eqs. (5), (6), and (7) show some of the relationship between the feature classes and their sub-classes. The subsets of classes features color, type are shown in relationships (5) – (7), respectively. For instance, the relationship (5) describes yellow, green, black are the subsets of color. Also the relationship (6) shows type, color are the subsets of leaves. The relationship (7) shows Apple, BellPepper, Botato, Cherry, corn, Grape, Orange, Peach, Raspberry, Squash, Strawberry are the subsets of type. Fig. 3 visually describes the hierarchical relation of the domain and features of EPDO Ontology.

$$yellow, green, black \sqsubseteq color, \quad (5)$$

$$type, color \sqsubseteq leaves, \quad (6)$$

$$Apple, BellPepper, Botato, Cherry, corn, Grape,$$

$$Orange, Peach, Raspberry, Squash, Strawberry \sqsubseteq type \quad (7)$$

4. Proposed method

The proposed method is classified into four phases. Fig. 4 illustrates the general workflow of the suggested method.

1) Segmentation and feature extraction phase.
2) connect features extraction with EPDO phase
3) Extracting threshold values phase.
4) Classification based on EPDO phase.

In the proposed method, the input is noisy image. We don't need to remove the noise from the input noisy image. So, the proposed method saves time and effort for removing the noise. Various kinds of noise may infect images like Gaussian, impulsive, speckle, or mixed noise. Image processing has several pre-processing stages. Image denoising is a major pre-processing stage in the image processing [34, 35].

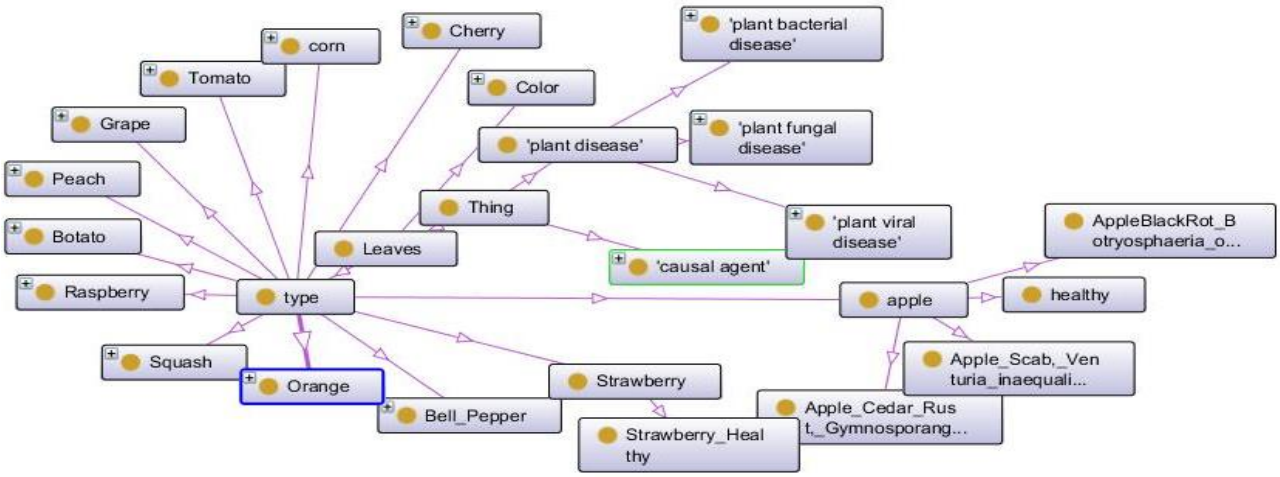

Figure. 3 The hierarchy of EPDO domain and features

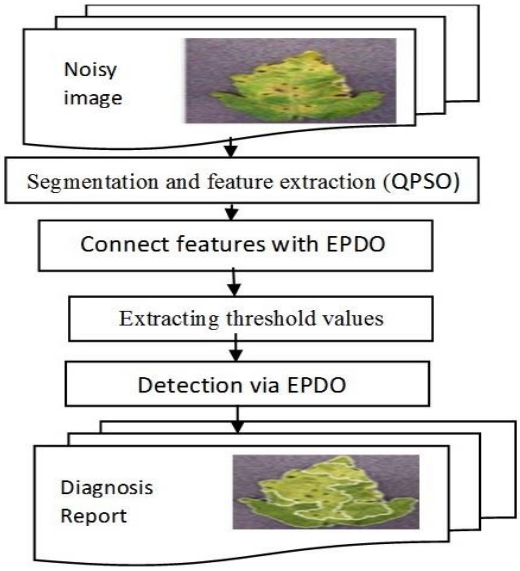

Figure. 4 The proposed method phases

The aim of denoising images is to remove noise from the damaged images in order to assess their initial image, while preserving the appropriate characteristics and useful information of images. Due to the enhanced performance of the noisy images that are damaged by multiple noise types, several image denoising algorithms have been enhanced in recent years. In [36, 37] A wider description of the denoising methods is provided. While there are different kinds of images denoising algorithms, their efficiency in reducing noise and running time is not optimal. The input images are the same, having the same size and damaged with the additive Gaussian noise (GN) $N(0, \sigma^2)$, where σ^2 is the estimated noise deviation with noise level $\sigma <= 70$ (experementally). This series of tests was designed to know whether the Ontology can actually identify the characteristics of noisy test image plant diseases after we inserted the noise, or whether it's just knowing the inherent biases in the dataset.

4.1 Segmentation and feature extraction phase

The segmentation is a significant and essential step; the image is split into objects that can be defined and categorized. The outputs of the segmentation method are image objects featuring as contextual, spectral, as well as geometric. As a collection of pixels, the segmented object may have geometric attributes like shape and size. In contrast, divided objects are contextually connected by spatial relationships. Extraction of features is the next stage in which varying numbers of features are determined for each segment of the object image. The determined feature values are transferred from Phase 1 in the proposed technique. The outcome of this stage is segmented image objects with feature values. The QPSO algorithm is applied to compute the appropriate parameters and then to identify the appropriate threshold values in this paper. In Ontology, the image objects, segmentation parameters and information are related to each other.

4.1.1. Image segmentation

4.1.1.1. Preliminaries

RGB has been transformed to pseudocolor (ind). As we can save a copy of the map used for that. We can convert each element of the pseudo-color map to grayscale and show it in that manner. At last, the pseudocolor map can be transformed to RGB. Without loss of information, we cannot immediately transform the grayscale images back to RGB. The input noisy image transformed into pseudocolor map

and then transformed the pseudocolor member into grayscale image. Let L is the grayscale levels of an image $[0,1,\dots,L-1]$. The grayscale levels L allocation is displayed in histogram $h(g)$. The histogram $h(g)$ appears as a distribution function of the probability in the following Eq. (8):

$$h(g) = \frac{n_g}{N}, h(g) \geq 0,$$
$$N = \sum_{g=0}^{L-1} n_g, and \ \sum_{g=0}^{L-1} h(g) = 1 \quad (8)$$

Where n_g is described as number of pixels with gray level g , and N is the complete pixel amount in an image. A combination of the Gaussian probability function is the histogram equation:

$$p(x) = \sum_{i=1}^{K} P_i p_i(x) = \sum_{i=1}^{K} \frac{p_i}{\sqrt{2\pi\gamma_i}} e^{\frac{-(x-\tau_i)^2}{2\gamma_i^2}},$$
$$\text{and} \quad \sum_{i=1}^{K} P_i = 1 \quad (9)$$

Where P_i is a class i probability, $p_i(x)$ is described in gray-level random variable x in class i, as the probability distribution function. The mean and standard deviation of i th the distribution probability function are τ_i and γ_i respectively, and K denotes the number of classes in image. The parameters $P_i, \tau_i \ and \ \gamma_i$ are calculated by using a Mean Square Error (MSE) criterion. The MSE from gray level random variable x_i $p(x_i)$ to $h(x_i)$ (histogram random variable x_i) is referred to as

$$E = \frac{1}{n} \sum_{i=1}^{n} [p(x_i) - h(x_i)]^2 \quad (10)$$

Where the histogram of n-point is considered [38]. The Eq. (9) has no recognized analytical solution but is non-linear formula. The gradient information can be resolved via iterative approach. Where, the numerical methods approach is iterative approach based gradient data. Depending on the initialization, the ultimate solution to a gradient descent approach is hard. The QPSO will therefore be applied to evaluate the appropriate parameters and to identify the appropriate threshold values.

Although multiple segmentation [3-8] models exist, the scientists experience a challenge of finding an effective technique of image segmentation. Despite advances in latest years there is uncertainty in the perceptual composition of image regions. In which the segmentation of images into the perceptual classification of image regions is really essential, as many apps rely on them such as scene comprehension, object detection, object identification and semantic image segmentation [33]. In the same manner as traditional methods, the suggested semantic segmentation method requires that image features have been linked by the statistical composition of the perceived setting and therefore uses clustering algorithms such as blurred c-means (FCM) as well as K-means to use separate vectors as cluster centrepieces. The features of the image will then be planned on the relevant bins. Finally, pixels form a region within the same cluster. Fig. 5 presents certain test images, which are segmented with the proposed method, and are similar to two state-of-the-art methods, JSEG [7] and SLIC [4]. The first row is the initial image. The second row is an outcome of the JSEG, the third row is an outcome of the SLIC while the last line a segmented image with the proposed approach. The outcomes achieved with the proposed method are more closely related to the visual perception of humans.

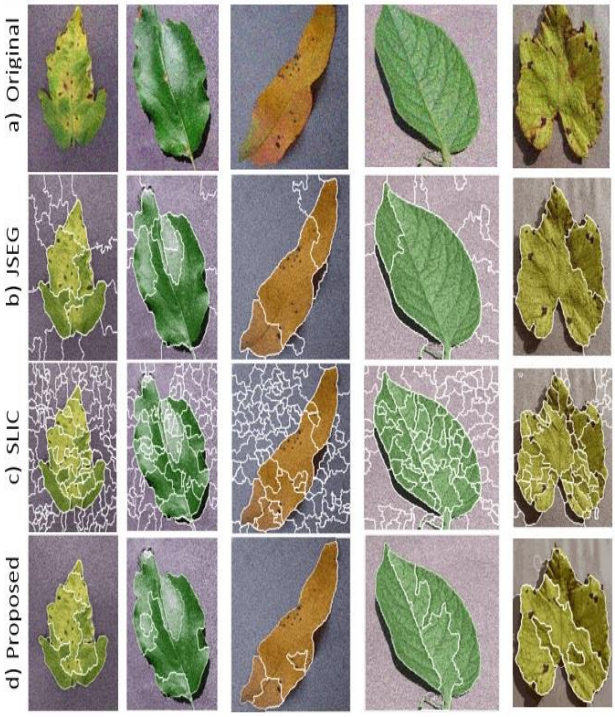

Figure. 5 illustrates examples and correlations with state-of-the-art techniques: (a) Initial image, (b) JSEG technique outcomes, (c) SLIC technique outcomes, and (d) segmented images using the technique proposed

4.2 Extracting threshold value

After using the QPSO all parameters in Eq. (9) can be evaluated in the results of the appropriate threshold. The threshold results can be evaluated after measurement of the total probability error for two Gaussian neighboring functions.

$$E(T_i) = P_{i+1}E_1(T_i) + P_iE_2(T_i), i = 1,2,3, \dots, K-1 \quad (11)$$

Where,

$$E_1(T_i) = \int_{-\infty}^{T_i} p_{i+1}(x)dx, \quad (12)$$

$$E_2(T_i) = \int_{T_i}^{-\infty} p_i(x)dx \quad (13)$$

The probability of error in classifying pixels in class (i+1)th to class $(i)^{th}$ as well as in class $(i)^{th}$ to class (i+1)th are $E_1(T_i)$ and $E_2(T_i)$ respectively. T_i is the threshold value from class $(i)^{th}$ to class $(i+1)^{th}$. After selecting T_i the $E(T_i)$ is minimal. The following Eq. (14) is applied to calculate the optimal T_i:

$$AT_i^2 + BT_i + C = 0 \quad (14)$$

Where

$$A = \gamma_i^2 - \gamma_{i+1}^2,$$
$$B = 2\left(\tau_i\gamma_{i+1}^2 - \tau_{i+1}\gamma_i^2\right),$$
$$C = (\gamma_i\tau_{i+1})^2 - (\gamma_{i+1}\tau_i)^2 + 2(\gamma_i\gamma_{i+1})^2 \ln\left(\frac{\gamma_{i+1}P_i}{\gamma_iP_{i+1}}\right). \quad (15)$$

There are two potential solutions in the earlier quadratic equation; only one of them can operate.

4.3 Classification and connecting to EPDO

Where the noisy input image is segmented, and features are extracted after phase 1. In phase 2, these features will compare with the features that existed in EPDO, if they are same the input noisy image will classify, and its disease, type and color will detect.

Semantic Web Rules Language (SWRL) has been applied to write the rules of ontology. Modularisation of ontological rules is applied to distinguish domain and feature classes identification rules. It aims to separate generic rules from localized rules which alter with provided datasets. These rules that applied to classify the plant diseases are focused on the SWRL. In SWRL, there are two components of the rules 1) an antecedent, 2) consequent, the two components consisting of a set of atoms. The atoms can be shape $\mathrm{C(x)}, \mathrm{P(x,y)}, \mathrm{sameAs(x,y)differentFrom(x,y)}$, or $\mathrm{builtIn(r,x,\dots)}$, where the OWL description is C, the OWL property is P, r is a built-in relation, and x and y are two variables [39]. The consequent as well as an antecedent are written as $a_1 \wedge a_2 \dots \wedge a_n$. The question mark $(e.g., ?x)$ is referred to the variables. We may use SWRL to limit the number values of the factors to the built in *greater Than Or Equal* and *less Than*. For instance, in Eq. (16) the definition of a *healthy* states that they are found in *leaves* of *type* and *apple*. In Eq. (17), the definition of a *Peach Bacterial Spot,Xanthomonas campestris* states that they are found in *leaves* of *type* and *peach*. Also, the definition of *Orange Huanglongbing (Citrus Greening), Candidatus Liberibacter spp* that they are found in *leaves* of *type* and *orange*. We have a standard for ' plant disease ' as:

$$Thing(?x) \wedge Leaves(?x) \wedge type(?x) \wedge apple(?x) \rightarrow healthy(?x) \quad (16)$$

$$Thing(?x) \wedge Leaves(?x) \wedge type(?x) \wedge Peach(?x) \rightarrow \text{Peach Bacterial Spot, Xanthomonas campestris}(?x) \quad (17)$$

$$Thing(?x) \wedge Leaves(?x) \wedge type(?x) \wedge Orange(?x) \rightarrow \textit{Orange Huanglongbing (Citrus Greening), Candidatus Liberibacter spp}\ (?x) \quad (18)$$

These rules were applied to classify plants using Protégé 4.3.0. Each image segment was classified into each plant class. The outcome of the classification is a high level entry for segmentation and this method is referred to as EPDO-based ranking.

5. Experiment results

5.1 Data

Fig. 6 displays a distinct content of noisy images. For the uniformly chosen collection of leaves, Fig. 6 demonstrates distinct variants of the same leaf. No datasets are available and smaller datasets are not available for free. In attempt to fix this issue, we have been using the PlantVillage project, where tens of thousands of images of healthy as well as diseased plants are publicly and readily accessible. We used 49,563 noisy images in this paper for the classification of 12 plant species with 22 diseased or good ones. The efficiency of the proposed technique is evaluated in 29 possible categories depending on its capacity to identify the right couple crop diseases.

Dataset: the proposed method on the [2] database is being computed. The plan PlantVillage [2] offers an overview of 49, 563 images of 12 plant species (or healthy) with 22 diseases, allocated to them with a variety of 29 class labels. The class label corresponds to a couple of plant disease; it only takes the image of

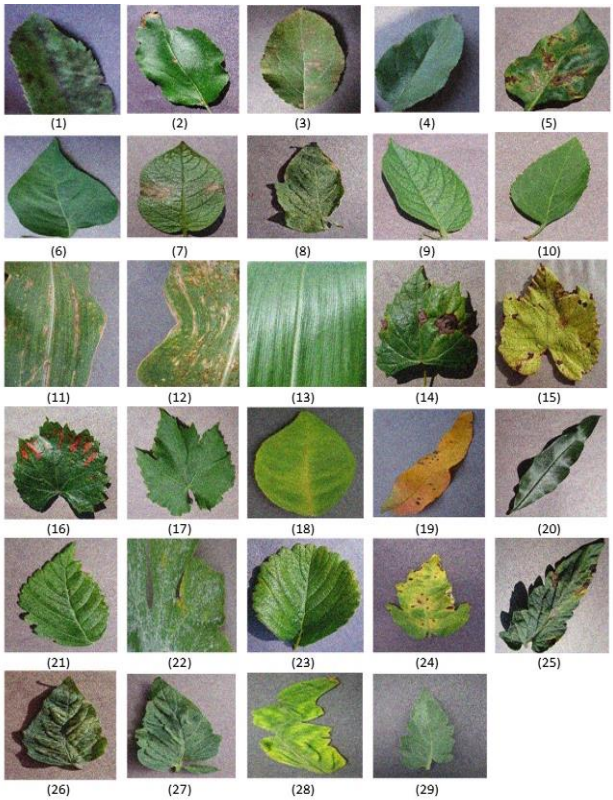

Figure. 6 Leaves images from the PlantVillage dataset, representing every plant-disease pair used: (1) Apple Scab, Venturia inaequalis, (2) Apple Black Rot, Botryosphaeria obtuse, (3) Apple Cedar Rust, Gymnosporangium juniperi-virginianae, (4) Apple healthy, (5) Bell Pepper Bacterial Spot, Xanthomonas campestris, (6) Bell Pepper healthy, (7) Potato Early Blight, Alternaria solani, (8) Potato Late Blight, Phytophthora infestans, (9) Potato healthy, (10) Cherry healthy, (11) Corn Gray Leaf Spot, Cercospora zeae-maydis, (12) Corn Common Rust, Puccinia sorghi, (13) Corn healthy, (14) Grape Black Rot, Guignardia bidwellii, (15) Grape Leaf Blight, Pseudocercospora vitis, (16) Grape Black Measles (Esca), Phaeomoniella aleophilum, Phaeomoniella chlamydospore, (17) Grape Healthy, (18) Orange Huanglongbing (Citrus Greening), Candidatus Liberibacter spp., (19) Peach Bacterial Spot, Xanthomonas campestris, (20) Peach healthy, (21) Raspberry healthy, (22) Squash Powdery Mildew, Erysiphe cichoracearum, (23) Strawberry Healthy, (24) Tomato Bacterial Spot, Xanthomonas campestris pv. Vesicatoria, (25) Tomato Early Blight, Alternaria solani, (26) Tomato Two Spotted Spider Mite, Tetranychus urticae, (27) Tomato Mosaic Virus, (28) Tomato Yellow Leaf Curl Virus, and (29) Tomato healthy

the plant leaf to identify the crop disease pair. The plant disease pair description from the PlantVillage dataset is displayed in Fig. 6.

Features, Baselines and Metrics: the efficiency of the method proposed is comparable with state-of-the-art classification accuracy methods. These state-of-the-art approaches include the Layered object [40, 41], Contextual cues [42, 43], Harmony [44], SvrSegm [45], HIM [46], DPG model [47], and Graphical model [48]. In [2], the performance is computed based on the ratio between intersection of the inferred segmentation and the ground truth, and of their union as Eq. (19).

5.2 Validation

Comparison of the ground truth data with classification result known as validation. Total precision of classification results has been measured by method of a confusion matrix Eq. (19) [33].

$$total\ accuracy = \frac{TP}{TP+FP+FN} \tag{19}$$

Where TP is True Positives, FP is False Positive, and FN is False Negative pixels. By validating the classification outcomes, TP, FP, as well as FN are calculated by validating the classification results against the ground truth data.

In the experiment, the visual features of the superpixels of the training samples are used (color, texture and shape). In the SLIC algorithm, the full amount of superpixels is equal 1000 to over-segment images into uniform superpixels. The shape feature, which differs from the color and texture of irregular superpixels, is captured from regular -shaped semantic object parts because the form descriptors mostly depend on edges and contours. The visual features from the samples (589,483 samples for color and texture, and 9,750 samples for shape feature) in the PlantVillage were subsequently acquired are utilized in the proposed method for clustering. In Tables 2, 3, and 4 describe the outcomes of our classifications. The confusion matrix of the 5 classes is shown in Table 2. In the confusion matrix, in the first row the labels display the classifier predictions, although in the first left column the ground-reality labels are displayed. The input ' 6 ' for instance in the third row shows that six test samples have been estimated as peach, but are indeed of the Potato class. The diagonal records display right results (the expected and the ground truth labels match). Where the right predictions are the diagonal entries.

Table 2. Confusion matrix for the training set

Classifier Ground truth	Orange	Potato	Peach	Grape	Tomato
Orange	1674	19	7	4	2
Potato	15	1320	6	12	5
Peach	1	7	932	22	6
Grape	1	1	5	1064	8
Tomato	3	7	2	6	410

Table 3. Displays outcomes for various approaches for classification on [2]

Image No. / Algorithms	1	2	3	4	5	6	7	8	9	Avg.
Layered object	71	68	73	76	78	77	80	81	82	76.2
Contextual cues	88	92	80	74	86	75	85	80	81	82.3
Harmony	62	89	87	**83**	81	83	84	83	85	81.9
SvrSegm	80	83	78	77	80	**84**	82	82	84	81.1
HIM	65	94	84	81	76	81	81	79	74	79.4
DPG model	79	83	68	75	77	79	77	80	80	77.6
Graphical model	76	90	67	59	70	55	75	59	78	69.9
EPDO	**89**	**95**	**89**	76	**87**	83	**87**	**84**	**86**	**86.2**

* The better outcomes are marked by bold.

Table 4. Some properties of plant images that identified using the proposed approach

Features / Image No.	Color	Name	Diseases
1	May be black or green	Apple Scab	Venturia inaequalis
2	green	Apple Black Rot	Botryosphaeria obtusa
3	green	Apple Cedar Rust	Gymnosporangium juniperi-virginianae
4	green	Apple	Apple healthy
5	green	Bell Pepper Bacterial Spot	Xanthomonas campestris
6	green	Bell Pepper	Bell Pepper healthy
7	green	Potato Early Blight	Alternaria solani
8	green	Potato Late Blight	Phytophthora infestans
9	green	Potato	Potato healthy
10	green	Cherry	Cherry healthy
11	Green	Corn Gray Leaf Spot	Cercospora zeae-maydis
12	May be green or yellow	Corn Common Rust	Puccinia sorghi
13	green	Corn	Corn healthy

The efficiency measurements of the proposed technique and of the state-of -the-art techniques on the database [2] are displayed in Table 3. In the first row of the labels the tested image appeared, while in the first left column labels the state-of - the-art algorithms are displayed. As shown in Table 3, in the seven images of 1, 2, 3, 5, 7, 8 and 9, the proposed technique achieves high accuracy compared to the other methods at 86.2 % while the second-ranked method, i.e., the contextual cues was 82.3%. The layered object model, using instance color models and estimating the spatial arrangement of individual objects, works very well in classes like the potato, where the appearance of an instance varies significantly between different instances. Instead of using a far simpler method, the DPG model avoids spatial and global limitations, leveraging the global characteristics of the entire image. But still the average accuracy of DPG model is only 77.6. This is however still greater than the layered object models. The SvrSegm technique achieves 81.1. It is only focused on bottom-up data to merge several hypotheses of figure-ground segmentations with a large object spatial for sequential object labelling. Similar to experiments on the PlantVillage, the findings reported in Table 3 shows that greater level data produces more effective semantic labelling. However, it should be noted that it is difficult by itself to leverage higher order dependencies. This is, however, well managed in EPDO by including semantic correlations at the proper levels. Another important aspect is that the other techniques do not take individually consideration of the importance of each feature, which could be a cause of the errors. When ontological relations in EPDO are extracted, it is not only possible to represent the relationships between features, objects and concepts, but also to increase the discriminatory characteristics of ontology. Our model is more comfortable than the other models with the feature set (RGB, Gabor, and Tamura). This is possibly because it contains specific color, texture and shape features. However, it is noted, the feature combination regarded in EPDO is the principal option for describing domain knowledge in the lower space. More significantly, using various EPDO feature sets, the findings are still similar to the state-of-the-art advanced methods. In addition of global precision, the approach proposed also outperforms other approaches. Contextual cues [42, 43] merging high- and low-level characteristics Contextual cues and using the conditional random field (CRF) are 85% accessible. An established CRF hierarchical structure for combining contextual data on varying scales is the harmony potential technique

[44] that reaches 84%. 82 % and 76 % respectively were the resulting of HIM [46] and Graphical model [48]. Layered object's [40, 41] overall accuracy reaches 81 %. The SvrSegm [45] and DPG model [47] are 83% and 81% respectively of the global accuracy. 88% of the proposed approach are superior to other approaches, likely because of the consistency of the semantic implementation, weighting of features and the implementation of data and knowledge required.

Table 4 provides samples of outcomes which are found using the proposed approach for the 13 plant images. In Table 4, the labels in the top first row display the features that identified for each test image, while the tested image names are appeared in the first left column labels. For instance, the third row represents the color, name, and disease that detected when the noisy image No. '2' executed in the proposed approach.

6. Conclusion

As per the essential of quick treatment of plant diseases from corrupted images. This paper proposed approach for semantic image segmentation which used Ontology and Quantum particle Swarm Optimization. The approach proposed needs Ontology for the domain of interests to be constructed. Domain knowledge of plant characteristics can be extracted from Ontology. We use the PDO Ontology to improve our method and to perform all Ontologies required for logical descriptions by using existing terms. This paper offers an Ontology – based semantic image segmentation method (EPDO), which effectively uses distinct kinds of data at the proper levels. It connects low- and high-level features by integrating semantic understanding towards a gradual process from the very start. The QPSO algorithm is used to evaluate the appropriate parameters and then to identify the appropriate threshold values in this paper. Also, the proposed method EPDO has been produced, in part, thought merging terms and axioms from PDO with new classes, axioms, individuals, rules, and terms that describe plants and its diseases. The proposed method EPDO does not need to remove the noise from input images. It can detect the plant diseases in spite of the input image is noisy. So, it serves the time and effort needed to remove the noise from input noisy image until noise level σ=70. The proposed method EPDO is applied to 49,563 images from healthy and diseased plant leaves, it detected 12 plant species and 22 diseases. The overall results displays that the proposed method performs relatively well compared to the state-of-the-art.

The proposed method outperforms the state-of-the-art algorithms in terms of a global accuracy. The proposed method achieves 88% which is superior to other approaches, likely because of the consistency of the semantic implementation, weighting of features and the implementation of data and knowledge required. Our results show that a classification based on the proposed method is better than the state-of-the-art algorithms. One of the main advantage of the proposed method EPDO is the Ontology deduction is that it can deal with various kinds of relationships at distinct rates of neighbourhood and abstraction levels, which makes it relevant to other apps. Also, the proposed method and ontological inference contain features can be found in other apps such as image retrieval or pattern recognition and other areas like biomedical and geospatial picture analyses.

This research helps to enhance the use of Ontological techniques for the detection and development of plant diseases. It offer a new approach, which is used Ontology classification rules, to immediately extract threshold values. The current outcomes indicate that the approach proposed is stronger than the state-of-the-art approaches.

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