Semantic-Search: A Knowledge-Driven Classification Method for Plant Diseases

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***Abstract*—To efficiently detect plant diseases, A-CPS have been integrated with image processing mechanisms built on deep learning and CNNs. But these methods are Data Driven and need lots of labeled data per class. These models learn features specific to each class and need to be retrained to add any new class. In contrast, we present a Knowledge-Driven approach where the CNNs are used for cognitive computing so that it can semantically understand the patterns of the disease on the leaf. These semantics (features) will be used to query a manually created database containing semantic descriptions of diseases for disease classification. Since the model has cognitive abilities to describe the presented disease, adding a new class will need a simple database update instead of retraining on numerous images. The proposed Semantic-Search was validated on the PlantVillage database with 2000 images of 20 different diseases from 5 types of plants and achieved an accuracy of 94%.**

I. Introduction

To protect the yield of the crop, Agriculture Cyber-Physical Systems (A-CPS) [1] were integrated with imaging techniques [2] to capture images and classify the disease using machine learning [3], [4]. Machine learning approaches use Convolutional Neural Networks (CNN) or morphological operations to detect patterns specific to each disease and classify them with greater accuracy. To learn the features of diseases, they need to be trained on numerous labeled images per each class [5] as depicted by Figure 1. This approach of learning from large sets of data is termed as "Data Driven Approach". As there are large number of plant types and various diseases in each of them, developing a model that can detect all the diseases needs a huge number of labeled images. Acquiring and labeling such large datasets is not feasible. Also, adding a new class to the classifier in case of a newly identified disease needs new labeled data and computationally intensive retraining.

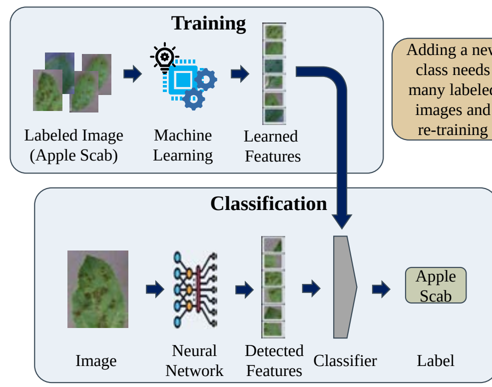

Figure 1: Illustration of Data Driven Approach.

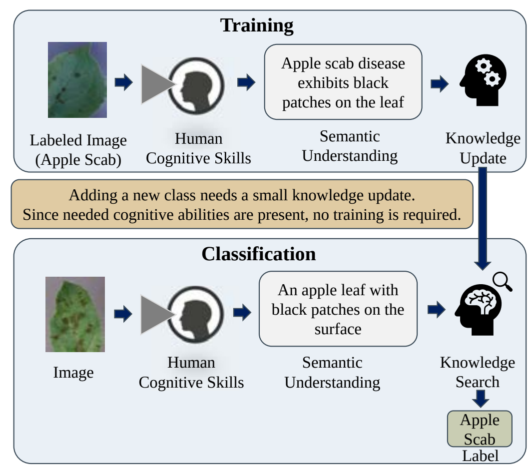

Figure 2: Illustration of Knowledge-Driven Approach.

Conversely, humans identify and classify images in a "Knowledge-Driven Approach" as shown in Figure 2. By default, humans have the cognitive abilities to detect patterns in an image and semantically understand any type of image. With the identifies pattern and semantic understanding of the image, humans search in their memory/knowledge to classify the image. In case of learning a new class/object, no changes will be needed in the cognitive processing, only a small update to the knowledge.

Along the similar lines, this paper presents a novel knowledge-driven approach [6] with semantic understanding for classifying plant diseases. The rest of the article is structured as follows: Proposed solution and its novel contributions are presented in Section II followed by a brief review of related works in Section III. Proposed method is detailed in Section IV with results presented in Section V while Section VI concludes the article with directions for future research.

II. Novel Contributions of the Current Paper

A. Proposed Solution of the Current Paper

Though there could be numerous diseases affecting all plants collectively, each disease is just a combination of a few visual features like patterns, shapes, textures, and colors. For example, Apple Scab and Grape Leaf Blight exhibit brown to black spots on the leaf. So, by understanding the disease semantically and searching the knowledge base with the information, most of the diseases can be classified. To emulate this human way of classifying images, this articles proposes a knowledge-driven system as shown in Figure 3. The neural networks in this system are trained to detect these semantics (patterns, shapes, textures, colors) present in leaves and semantically describe the disease. On the other hand, an expert creates a database for all plant diseases with their semantic features. By querying this data base with identified information, the disease can be classified. Since the model already has the cognitive abilities, adding a new disease class will just need a database update instead of retraining.

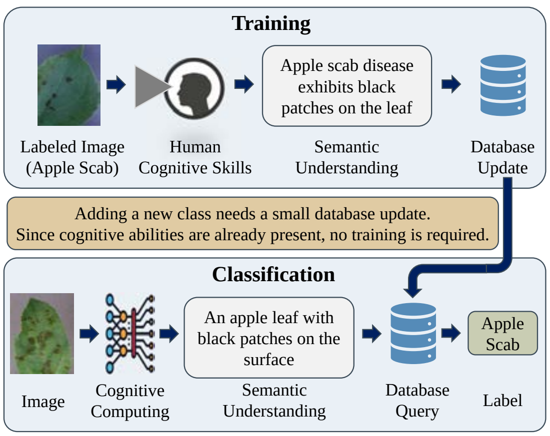

Figure 3: Proposed Knowledge-Driven Approach.

B. *Novelty and Significance of the Proposed Solution*

The novel contributions of Semantic-Search are as follows.

1) Semantic Understanding: The proposed method focuses on detecting patterns, objects in the diseased part, and the semantic description of the disease, rather than tightly coupling the model with features of individual disease.
2) Knowledge-Driven Approach: The classification proposed is driven by knowledge rather than data so that adding or removing a class can be achieved by a simple database update .
3) Interpretability and Explainability: Semantic-Search also presents the description of the disease to the user, explaining the classification decision as opposed to black box methods.
4) Generalizability: Since the proposed neural networks have the cognitive ability to detect semantics present in plant diseases they can be used for any plant and any disease.

III. Related Prior Works

Instead of classifying images with CNNs and strict conditions related to visual features (data driven), many researchers proposed methods to classify images by their content. The article [7] proposed a method to extract the texture feature vector of the presented image and classify it by a neural network. Authors of [8] presented image classification by histograms where color histograms are classified by a SVM. A classification similar to human perception is presented in [9] and [10] where low-level features are used to classify the image. Bag of visual words has been used to classify scenes in [11]. They represented findings in the image as a histogram of words and presented them to SVM for classification. Authors of [12] proposed usage of semantic attributes to overcome the limitation in bag of words. In a given image there could be more than one object, the relation between them can become instrumental in classifying it. This property of images has been explored in articles [13], [14] by developing knowledge maps to embed the relation between objects and traversing them with the objects identified to classify the image. Similarly, [15] discussed an ontology-based method to classify plant diseases based on findings from the farmer. Unlike the above methods, the proposed method does not train a classifier or needs complex knowledge maps. It uses CNNs to induce cognitive abilities and a relational database as a knowledge base for classification employing a simple structured query.

Table I: A brief summary of relevant literature.

Research	Method adopted	Remark
Park et al. [7]	Texture features classified by neural network	Lacks semantic understanding
Agrawal et al. [8]	Color histograms are classified by a SVM	Lacks semantic understanding
Vailaya et al. [10], [9]	Low level features are used hierarchically to classify image	Adding new class needs retraining of Bayesian networks
Yang et al. [11]	Bag of visual words	Lacks semantic understanding of image
Su et al. [12]	Bag of visual words and semantic attributes	Adding a new class needs re-training
Marino et al. [13] and Menglong et al. [14]	Searching knowledge map with objects detected in the image	Implementing and traversing knowledge maps is complex
Jearanaiwongkul et al. [15]	Ontology based classification using farmer's findings	Not fully automated, farmers findings are used as inputs
Semantic-Search	**Semantic understanding with knowledge base search**	**Has semantic understanding and does not need retraining**

IV. Proposed Method

As mentioned in Section II-A, instead of developing a model that learns features specific to each disease, we tried to develop a model that can list out semantics (features) and semantically describe the disease. Generally, any plant disease can be described as combination of few patterns, textures, shapes and colors. So, we examined about 20 different plant diseases to semantically describe each disease and hand pick the semantics to complete feature engineering process as presented in Table II and Table III respectively.

By performing a query in a database which has information of the diseases and name of the plant, the disease can be classified. So, multiple tables are created in the database for the engineered semantics: shapes, textures and colors. These feature tables are linked with the disease in many-to-many

Table II: A brief overview of few disease semantics.

Plant	Disease	Symptom	Semantics
Apple	Black rot	Flecks or lesions which are brown in the center and purple at margin	Objects: Flecks, Lesions Colors: Brown, Purple
Apple	Powdery mildew	White velvety patches on the underside of leaves	Texture: Velvety Color is redundant
Grape	Leaf blight	Small, brown-black spots	Objects: Spots Colors: Brown, Black
Tomato	Black mold	Appearance of black or brown lesions	Objects: Lesions Colors: Black, Brown
Tomato	Mosaic virus	Infected leaves exhibit dark green mosaic	Texture: Mosaic Color is redundant
Tomato	Blight	Yellow chlorotic lesions	Objects: Lesions Colors: Yellow

Table III: Overview of semantics engineered.

Semantics	Instances
Shape	Spot (Spots, Lesions, Patches), Flecks, Curls, Stripes
Color	Yellow, Purple, Orange, Black, Brown, White, Red
Texture	Powdery, Mosaic, Velvety

fashion. For each disease, a record is created in the database as shown in Figure 4.

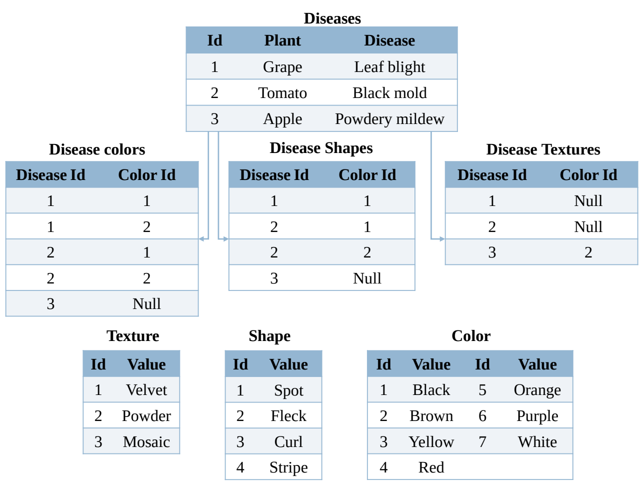

Figure 4: Entity-Relationship diagram of the database.

To classify in knowledge-driven fashion, we propose the use of CNNs which are trained on the engineered semantics presented in Table III. Most of the images have different backgrounds which can affect the classification. So, the leaf's boundaries are identified by fitting a contour around the leaf. Then, four regions of interest (ROI) are identified at the edges of the leaf and one region at the center of the contour. Disease textures occupy most of the leaf while objects are present in few parts and only the colors of the shapes are needed for classification. To address this, we propose using three separate shallow [16] CNN models that process the image sequentially, each focusing on different aspects of the image. Disease exhibiting texture can be classified by the texture and doesn't need additional semantics. Similarly, in the case of flecks and leaf curls, color semantics are redundant. So, we adopt a hierarchical approach shown in Figure 5 to analyze the image further only if additional information is needed. The thus identified semantics (features) are used to semantically describe the disease and classify it by querying the database represented in Figure 4.

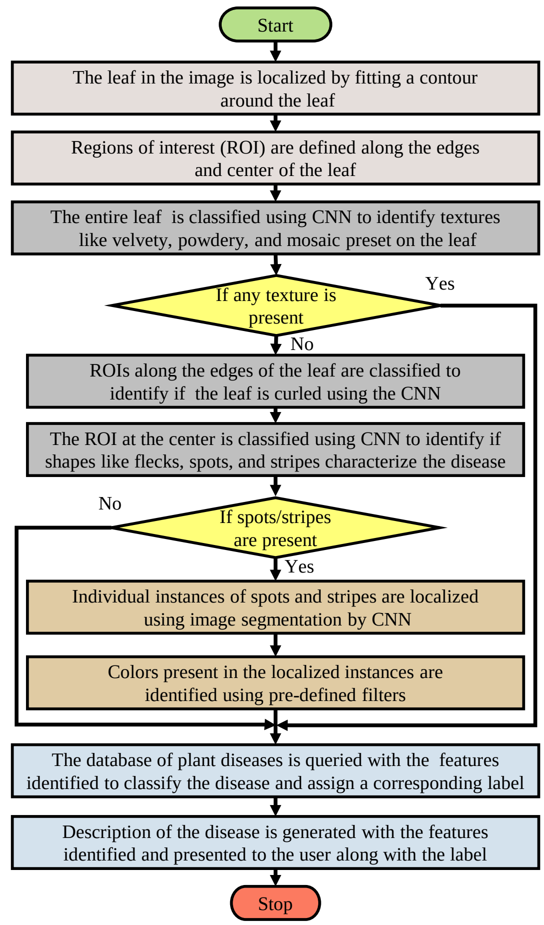

Figure 5: Working of proposed method.

V. Experimental Verification

The proposed Semantic-Search has been developed using Python and TensorFlow for CNN-based image classification, segmentation models, and SQLite to host a database for the knowledge base. It was validated on 2000 images of 20 different diseases from 5 types of plants in PlantVillage data set [17] and disease description from PlantVillage website [18]. This method attained an accuracy of 94% and results obtained for image of an Apple leaf with Ceder Rust disease are discussed here. To localize the leaf present in the image, a circular contour is fitted to the edges of the leaf using an active contour model from Scikit. Then, a rectangle of the maximum size possible inside this contour is drawn to define the central part ROI of the leaf and 4 more rectangles along its edges to define ROIs along edges of leaf as shown in Figure 6.

The entire leaf image is then presented to an image classification model to identify any textures present on the leaf. For the input image, no textures were detected as presented in

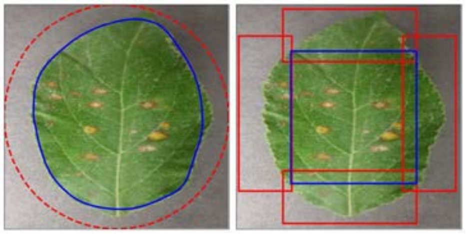

Figure 6: Input image with leaf localized and ROI defined.

Figure 7. So, the image has to be further diagnosed to classify accurately.

```
(1, 100, 100, 3)
Shape of images array: (1, 100, 100, 3)
1/1 [==============================] - 3s 3s/step
Teaxture of leaf is: Others
```

Figure 7: Predictions for leaf texture.

All the defined ROI are resized and presented to another image classification model to detect semantics like spots, stripes, flecks, and curls along the edges of the leaf. The presented image had spots and the same were detected by the model in Figure 8.

```
(5, 100, 100, 3)
Shape of images array: (5, 100, 100, 3)
1/1 [==============================] - 1s 1s/step
Teaxture of leaf in parts: Spots
Teaxture of leaf in parts: None
Teaxture of leaf in parts: None
Teaxture of leaf in parts: Spots
Teaxture of leaf in parts: None
The leaf has spots
```

Figure 8: Predictions for disease semantics.

As there can be multiple diseases with spots, the colors of the spots have to be identified to effectively classify the disease and the central part ROI is passed through a semantic segmentation which localizes (segmentation) these spots. For computational ease, instead of instance segmentation, semantic segmentation was performed and individual instances presented in Figure 9 are identified by connected component algorithm.

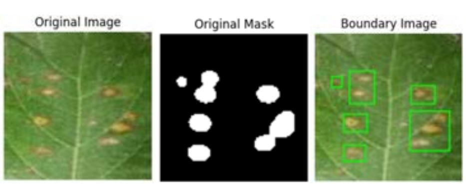

Figure 9: Segmented semantics found in image.

The identified instances are resized, smoothed and presence of predefined colors is detected by plotting histograms as in Figure 10. Yellow, Brown and Orange Colors were identified in the image presented.

As proposed in Figure 4, 7 different tables were created on SQlite, and records were added for colors, shapes, textures of the diseases in the data set as represented in Figure 11.

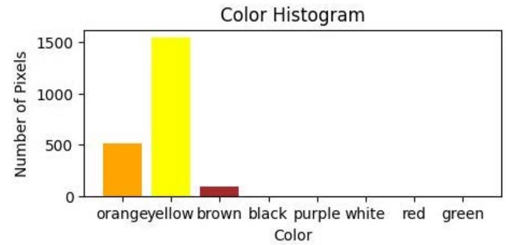

Figure 10: Histogram for the identified objects.

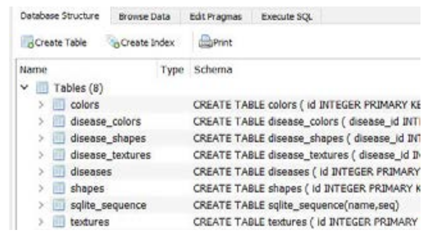

Figure 11: Database created on SQLite.

This database has been queried with the identified semantics (spots) and colors (yellow, brown, orange) along with the name of the plant (apple). The query returned ceder rust as shown in Figure 12. Thus, the proposed Semantic-Search successfully classified the presented image of apple leaf by using CNNs for cognitive computing and database for knowledge.

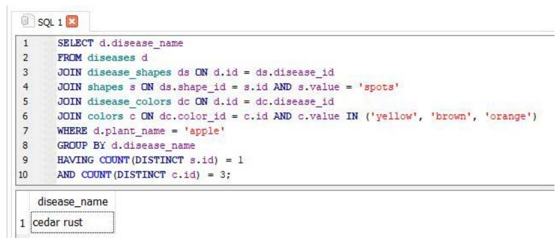

Figure 12: Result for the SQL query with semantics detected.

VI. Conclusion

In this paper, we presented a knowledge-driven approach for classifying plant diseases by semantic understanding. The proposed Semantic-Search learns to detect semantics and adding a new disease class does not need retraining of the CNNs. These predicions can be used in down stream tasks like identifying disease hot-spots [19] and quantifying the disease infestation [20]. Since the process of defining ROI in the leaf tries to find the largest rectangle possible inside the contour, in cases of narrow and curved leaves, the ROI defined could become smaller and may not include the diseased regions. In addition, the classification method used is static and does not change with semantics detected. Due to these limitations, the proposed method misclassified about 6% of the images. To overcome, these limitations, the usage of attention mechanisms and transformers to develop dynamic methods specific to the semantics present in the diseased can be explored in future works.

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