Conditional Multi-task learning for Plant Disease Identification

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Introduction

Plant diseases are a major threat to agricultural production, causing a severe food recession and affecting crop quality.

Problem statement:

- Existing approaches have been based on a method whereby the size of the network gradually increases as new classes are added, even if plant species or disease information is already available.
- It is not practical in a real application, especially to collect a complete set of images illustrating each species-disease pair.

Objective: To explore an alternative way of using the multitasking learning (MTL) mechanism in the identification of plant disease, replacing the traditional modeling of species-disease pairs.

Contributions:

- To show that our proposed conditional multi-task learning resulted in a better performance in plant disease classification compared to the usual CNN modelling approach.
- To compose a new dataset that covers the largest host species and diseases.

Dataset and Experimental Setting

Dataset:

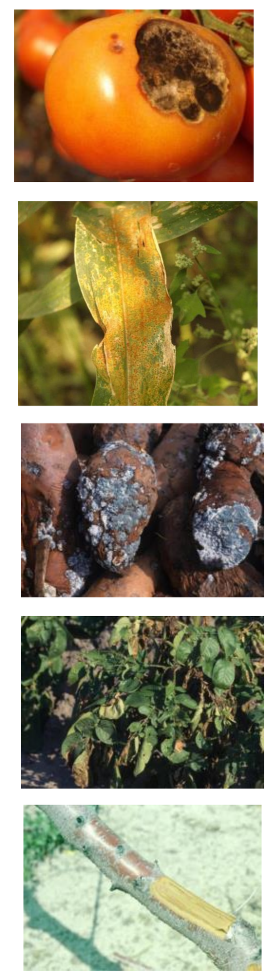
- A new plant disease identification dataset that covers the largest number of host species and diseases was composed by aggregating images from selected sources with verified labels.
- In exact, we have 1145 joint species-disease classes, 311 host species and 289 diseases.

Dataset	Number of training data	Number of testing data
PV [1]	594	146
Digipathos [2]	1668	345
IPM[1]	4522	812
Pl@ntnet	3540	663
Total	10324	1966

[1] Mohanty, Sharada P., David P. Hughes, and Marcel Salathé. "Using deep learning for image-based plant disease detection." *Frontiers in plant science* 7 (2016): 1419.

[2] Barbedo, Jayme Garcia Arnal, et al. "Annotated plant pathology databases for image-based detection and recognition of diseases." *IEEE Latin America Transactions* 16.6 (2018): 1749-1757.

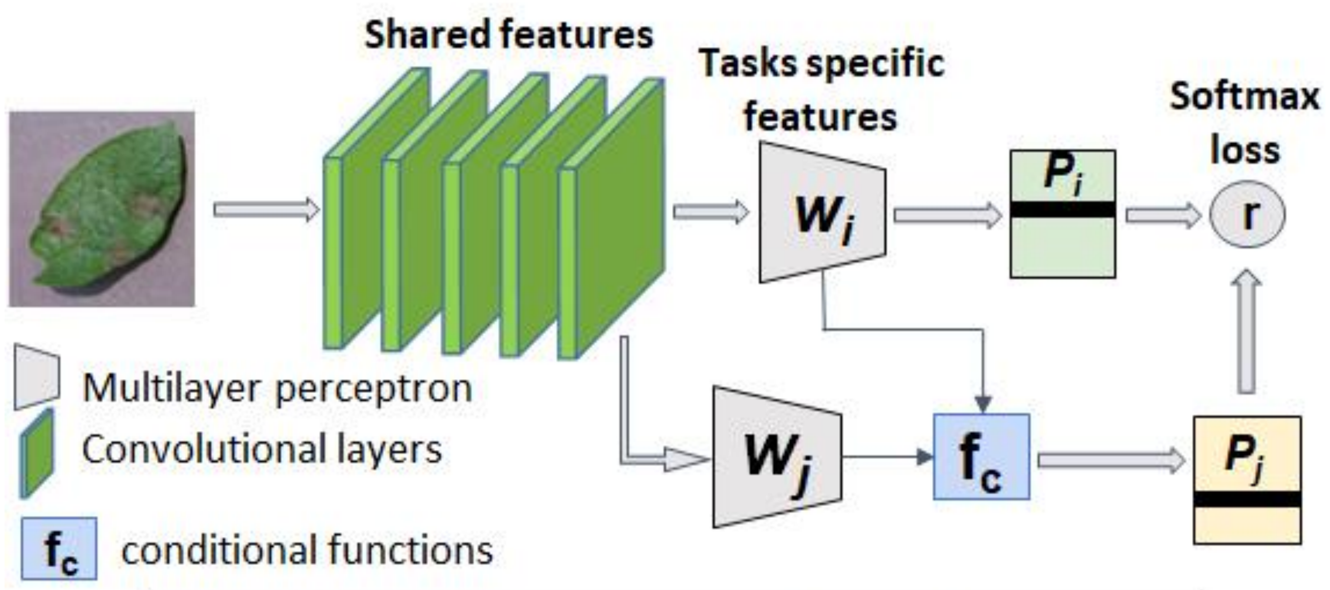
[1]https://www.ipmimages.org/

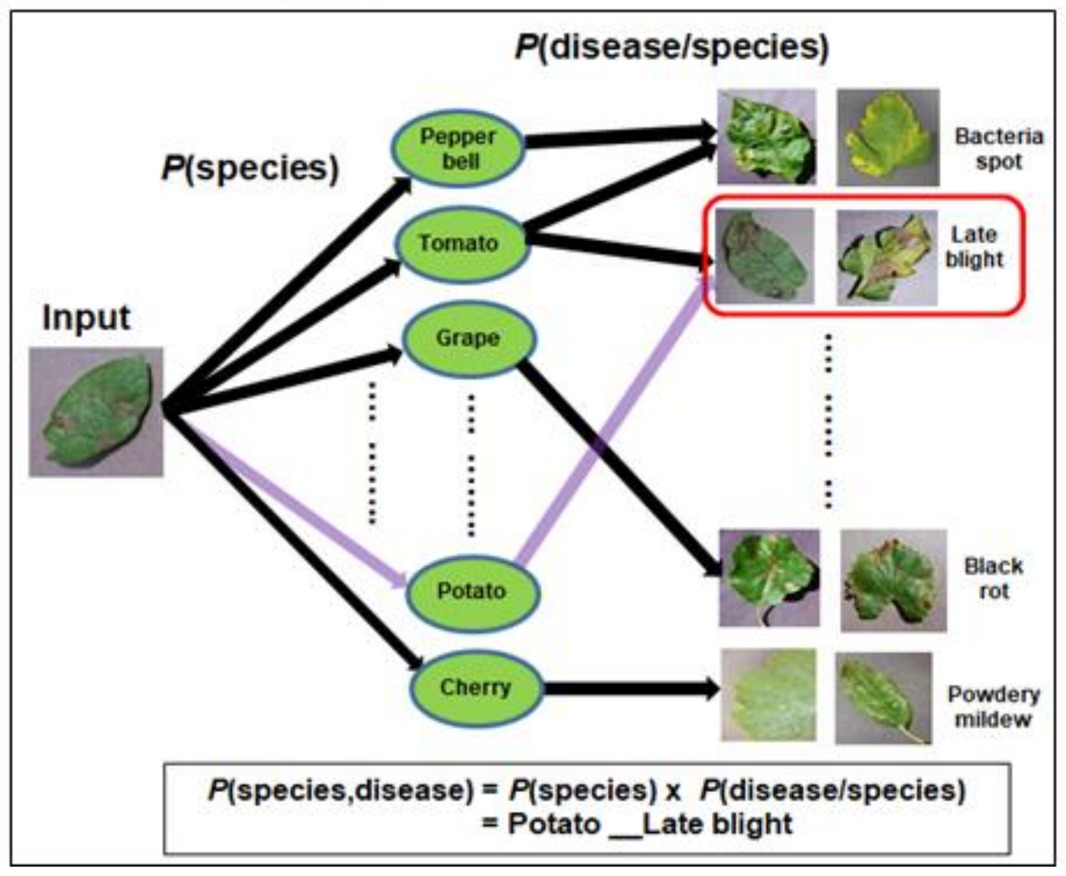


Experimental setting:

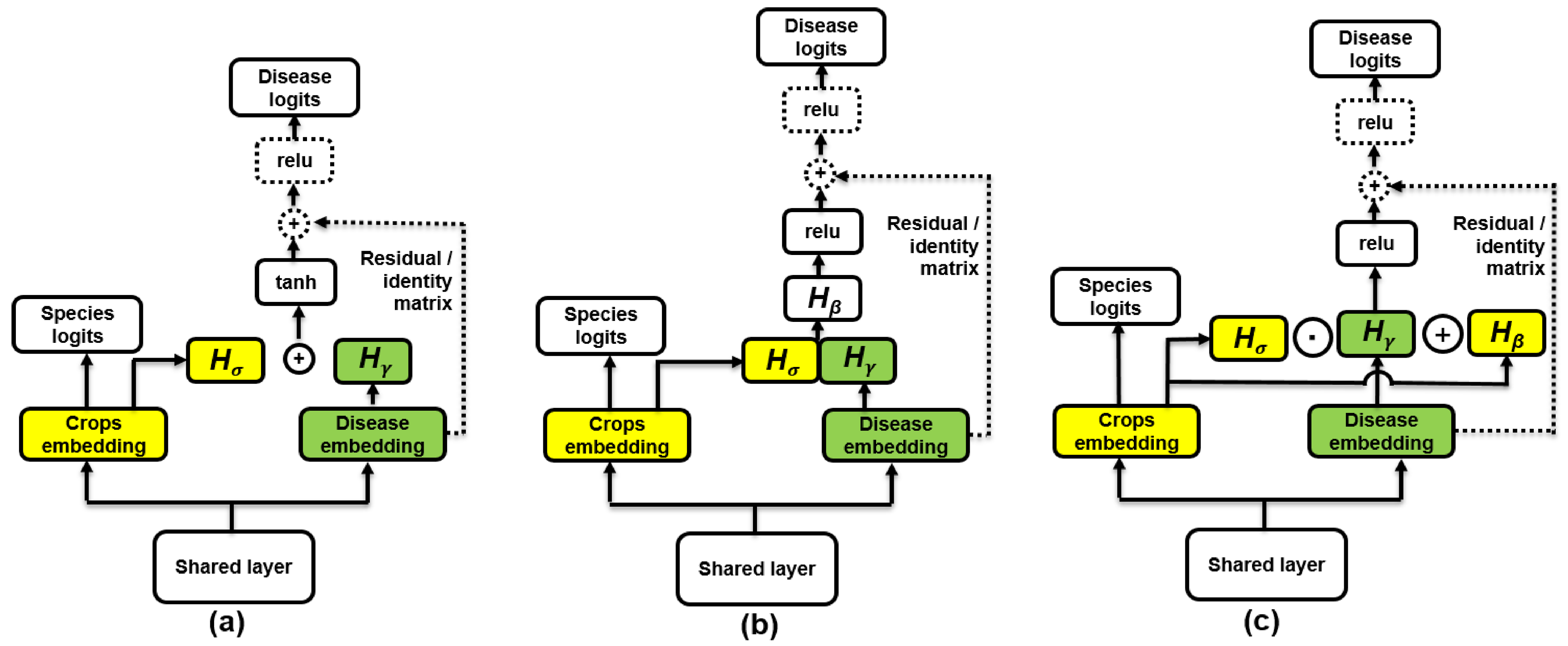
- Our network is based on Inception-V3, and the final activation layer were modified according to the different CMTL strategies proposed, as explained below.
- Models are formed using the Tensorflow framework and trained using an NVIDIA GTX1080 graphics card. The mini-batch size used is 45.

Methodology – Conditional Multi-Task Learning (CMTL)





- To model two main concepts/tasks which are host species and diseases through multi-task learning, and each concept is represented by its own feature distribution but they are strongly linked by a specific conditional structure.
- This structured process corresponds to the way plant pathologists use species information to infer the associated diseases.



Conditional feature fusion scheme: (a) Sum (FFS) and (b) Cascade (FFC) fusion, and (c) Conditional feature-wise linear modulation (FiLM). The identical mapping which is introduced to enrich the features of the disease layer is illustrated with dotted line.

Discussion and Conclusion

Discussion:

- Multi-task learning approach is more effective than the usual CNN modeling method (the joint net) for plant disease identification (Table 1).
- We could not conclude which CMTL-based approaches perform best as each approach achieved the highest accuracy in different datasets (Table 3).
- The dataset could serve as a benchmark for researchers working in the same fields.

Future direction:

- To address the problem of class imbalance.
- To detect potential unknown classes of diseases and species.

Our related publications:

- Lee, Sue Han, et al. "New perspectives on plant disease characterization based on deep learning." Computers and Electronics in Agriculture 170 (2020): 105220.
- Lee, Sue Han, et al. "Attention based Recurrent Neural Network for Plant Disease Classification." *In Press*, Front. Plant Sci., https://dx.doi.org/10.3389/fpls.2020.601250

Performance Comparisons

Table 1: Classification results of different model configuration

Configuration	Conjoint prediction	Disease	Host species
Conditional FFS-res	**69.43**	**82.96**	**78.64**
Conditional FFS	67.34	81.59	77.52
Conditional FFC-res	68.06	81.84	77.67
Conditional FFS	67.19	81.38	77.11
Conditional FiLM-res	68.01	82.15	76.91
Conditional FiLM	68.62	82.86	77.16
Generic MTL	68.16	82.76	76.96
Single nets	68.67	82.25	78.48
Joint net	68.82	82.15	76.70
Fashion net [3]	66.48	81.49	76.09

[3] W. Wang, Y. Xu, J. Shen, and S.-C. Zhu, "Attentive fashion grammar network for fashion landmark detection and clothing category classification," in Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition, 2018, pp.

Table 2: Classification results of the conditional FFS-res approach for different knowledge distribution

Configuration	Conjoint prediction	Disease	Host species
Conditional FFS-res	**69.43**	**82.96**	**78.64**
Conditional FFS	68.51	82.81	77.01

Table 3: The conjoint prediction from different model configurations on each dataset

Configuration	PV	Digipathos	IPM	Pl@ntNet	INRAE
Conditional FFS-res	93.84	85.80	64.16	**61.99**	8.76
Conditional FFS	91.10	86.09	61.70	59.28	**16.49**
Conditional FFC-res	**94.52**	**86.38**	61.82	60.33	16.24
Conditional FFS	**94.52**	84.64	60.47	60.33	13.40
Conditional FiLM-res	91.78	85.22	63.67	59.13	7.99
Conditional FiLM	93.15	83.77	**65.27**	59.43	9.28
Generic MTL	93.15	85.51	62.68	60.33	9.54
Single nets	93.84	84.35	63.18	61.69	2.06
Joint net	91.10	85.51	65.02	59.88	6.96
Fashion net [3]	90.41	84.64	61.70	57.62	13.40