EXPLAINABILITY IN GEOAI
A CHAPTER OF THE BOOK: HANDBOOK OF GEOSPATIAL ARTIFICIAL INTELLIGENCE

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Handbook of Geospatial Artificial Intelligence (GeoAI)

- Deadline: draft chapters will be due on the **Nov.15, 2022** (could be extended a little bit), final versions due in **early February 2023**, to be published by CRC Press/Taylor & Francis Group
- Table of Contents
  - **Foreword**
  - **Section 1: Background** (historical roots and general overview, philosophy of GeoAI, revisiting or new thinking of artificial intelligence in geography)
  - **Section 2: GeoAI methods and tools** (methodological foundations, spatial image processing, spatial natural language processing, spatial representation learning, intelligent spatial prediction and interpolation methods, deep learning for spatially heterogeneous datasets, spatial cross validation)

Handbook of Geospatial Artificial Intelligence (GeoAI)

- Table of Contents
  - **Section 3: GeoAI applications** (GeoAI for cartography and mapping, GeoAI for environmental remote sensing, GeoAI for social/urban sensing, GeoAI for humanitarian mapping, GeoAI for transportation, GeoAI for disaster response, GeoAI for public health)
  - **Section 4: Perspectives for the future** (**Explainability in GeoAI**, ethical and privacy issues in GeoAI, replicability and reproducibility in GeoAI, forward thinking on geospatial knowledge graph or GeoAI in general)
  - Appendix (A manifest of GeoAI tools)
- Requirement: usually about 6,000 ~ 8,000 words (including title, abstract, main content, figures, tables, and references) or could be shorter 3,000 ~ 4,000 words for certain topics

Our chapter: Explainability in GeoAI

1. Introduction

1.1. *What is explainability?*

Some key concepts (like interpretability and explainability); black-box models (machine learning, deep learning, artificial intelligence models); XAI methods

1.2. *Why do we use XAI methods?*

Explain the model decisions (verify the models and increase the confidence); capture the new knowledge (feature A is important to the task B); help improve the trained models

1.3. *Other items to be introduced*

For instance, local and global explanations, visualization of explanation (e.g., heatmap), explanation assessment, uncertainty

2. XAI methods

Basic principles of each category of methods (e.g., model-agnostic, gradient-based, layer-wise-based)

3. Applications of XAI methods in GeoAI

Three cases. The XAI methods are used to explain the model decisions, capture new knowledge, and benefit the model improvement

3.1. *Runoff forecasting in Germany*

3.2. *Distinguish between activities for weekdays/weekends*

3.3. *Plant species classification*

4. Discussion

design new XAI methods for GeoAI models; general knowledge mining (spatial heterogeneity); explanation assessment in GeoAI studies; visualization (human-friendly) of explanations

References

Applications of XAI methods in GeoAI

Cases	#1	#2	#3
XAI benefits	Explain model decisions	Knowledge mining	Improve the trained model
Task	Runoff forecasting	Distinguish human activities (weekday/weekend)	Plant species classification
Input data	Time-series of stations in Germany	Spatial distribution of taxi volume in Beijing	PlantVillage dataset
Model	LSTM+ (combine static features)	Customized CNN + FC	AlexNet
XAI methods	**???**	ST-LRP	Grad-CAM
Status	Trained model + results	Published paper	Published paper
Other		https://doi.org/10.1080/13658816.2020.1805116	https://doi.org/10.3389/fpls.2022.902105

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Case #1: Runoff forecasting in Germany

- Research area and data
  - Source: Helmholtz Centre for Environmental research
  - Mesoscale hydrological model (mHM) (Luis Samaniego et al., 2010)
  - Daily meteorological forcings (temperature, precipitation, ...) and basin physical characteristics called ancillary attributes (gridded!)

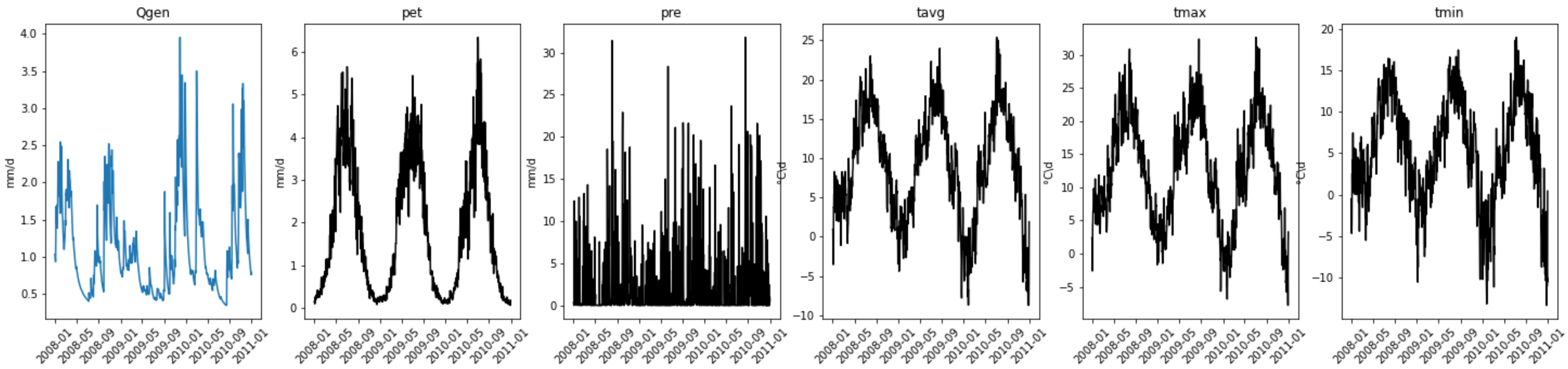


Figure: Daily surface runoff and meteorological forcings

Case #1: Runoff forecasting in Germany

- Task and model
  - Task: Approximation of the mHM model using daily meteorological forcings and ancillary attributes

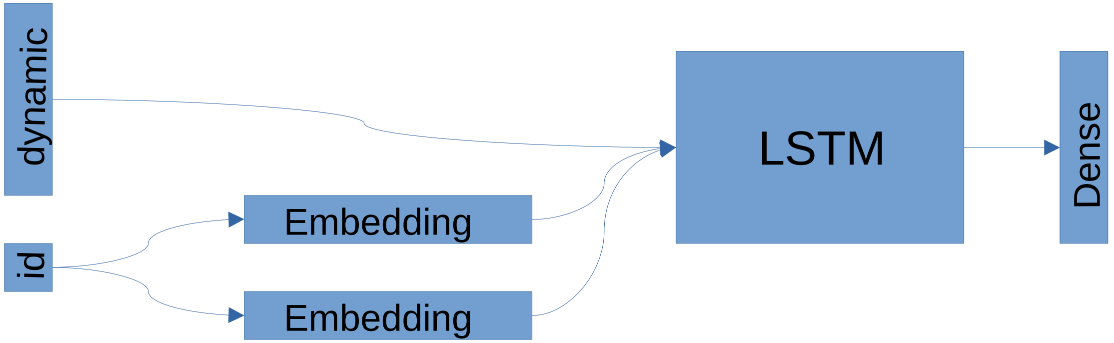


Figure: Graph of the LSTM using embedded station Ids as initial hidden and cell states

Case #1: Runoff forecasting in Germany

- Results

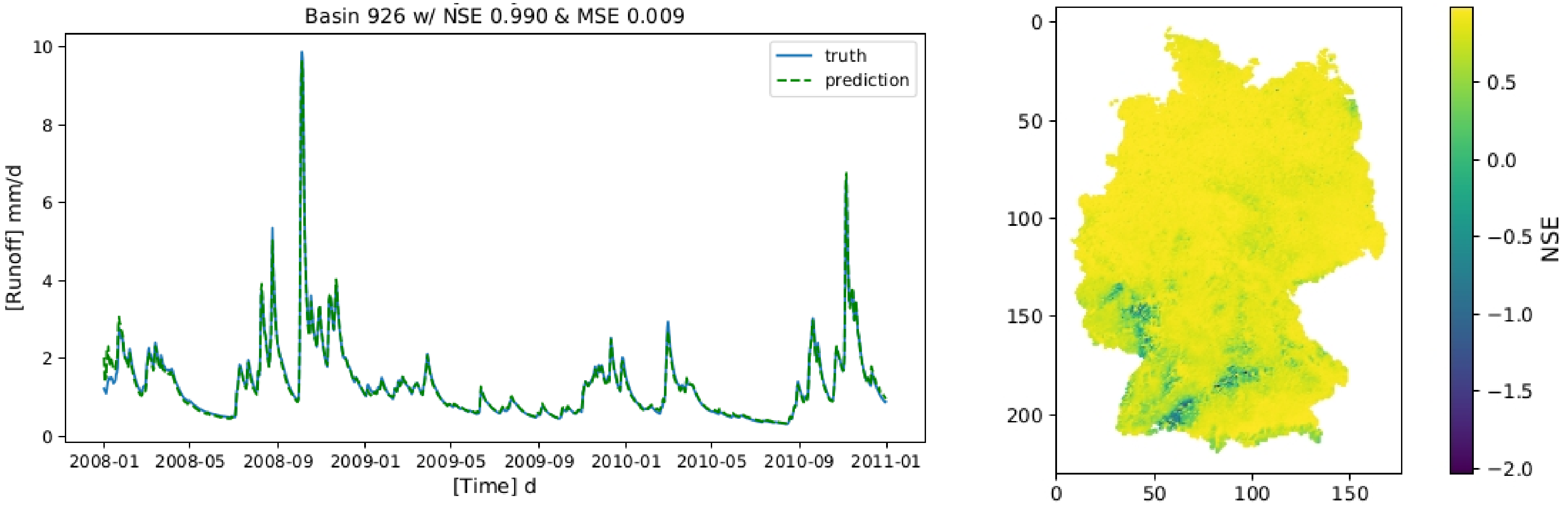
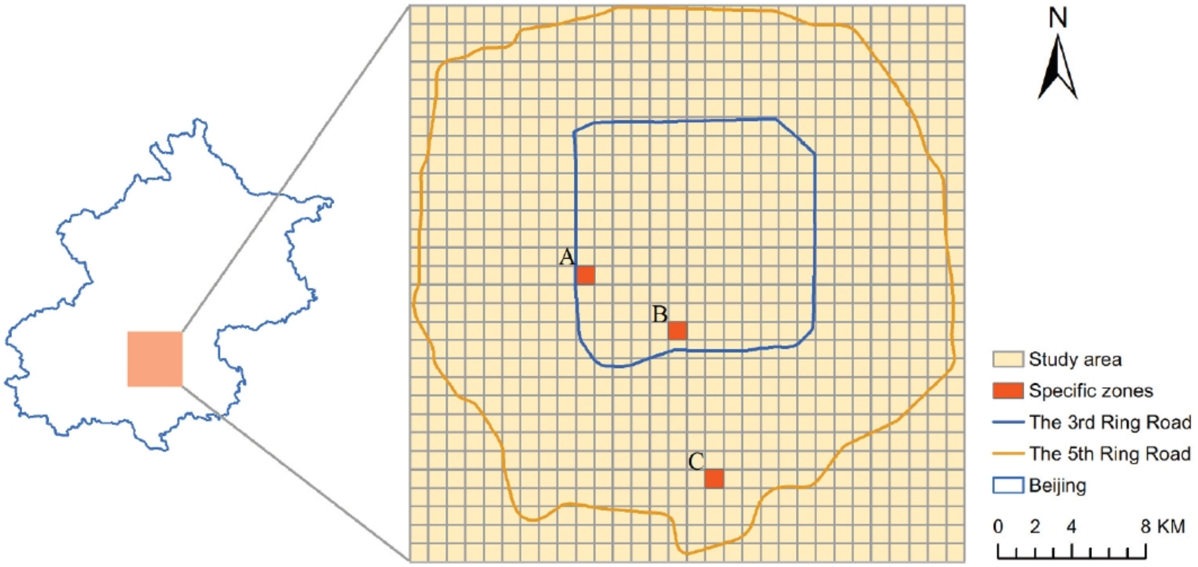


Figure: Approximation result from 2008 – 2011 for one gridcell (left). Overview of approximation results for Germany using the NSE metric (right)

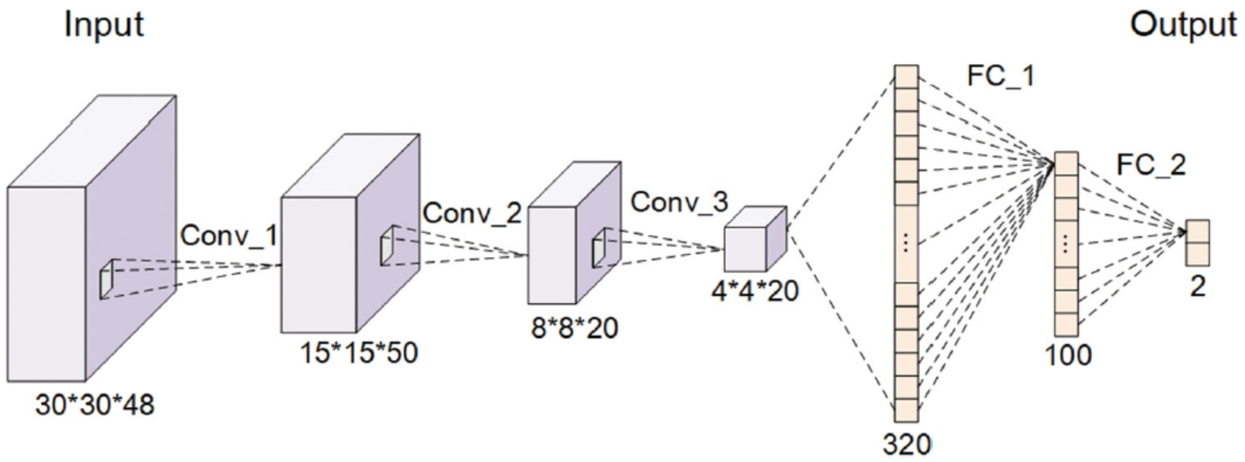
Case #2: Distinguish between activities for weekdays/weekends

- Research area and data
  - Raw data: Taxi origin and destination point (OD) data, Beijing, the entire year of 2016
  - Data processing: daily spatio-temporal distribution of point volume (30*30*48, 1km2, half hour)



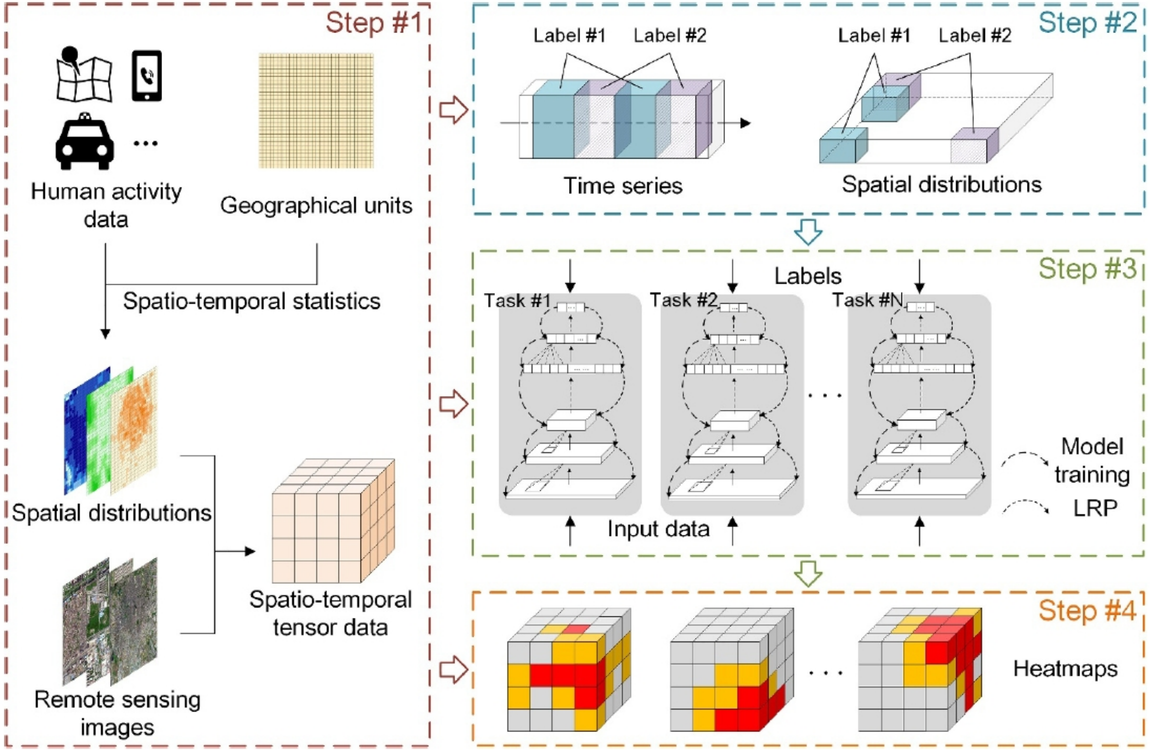
Case #2: Distinguish between activities for weekdays/weekends

- Task and model
  - Binary classification: activities distribution in weekdays or weekends/holidays
  - Performance: 98% in test data (first season in 2017)



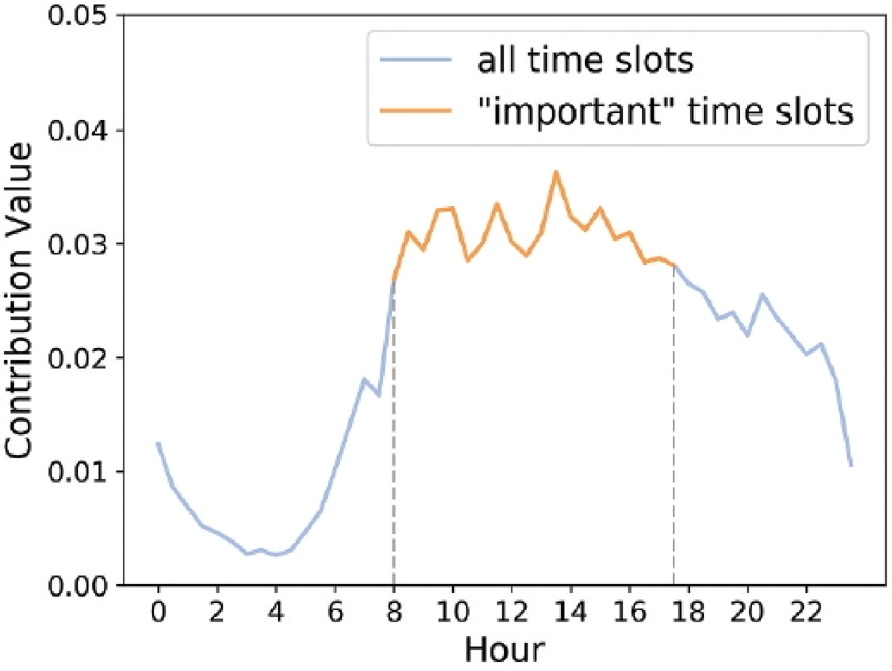
Case #2: Distinguish between activities for weekdays/weekends

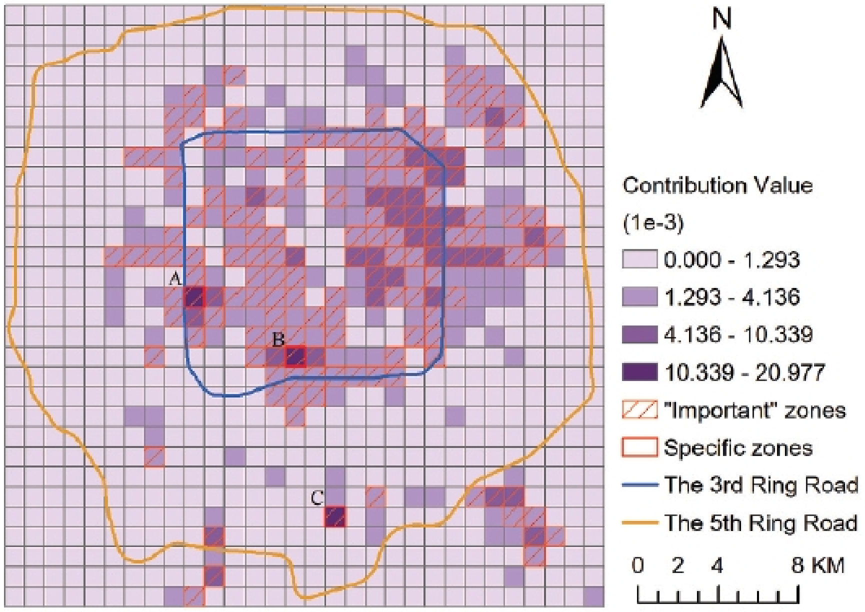
- ST-LRP method



Case #2: Distinguish between activities for weekdays/weekends

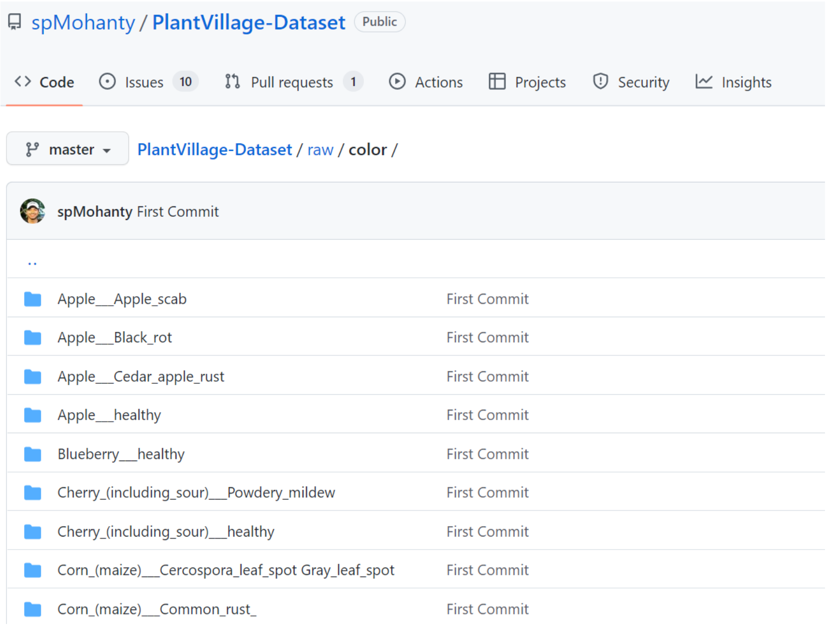
- Explanations (unit importance in temporal and spatial dimensions)

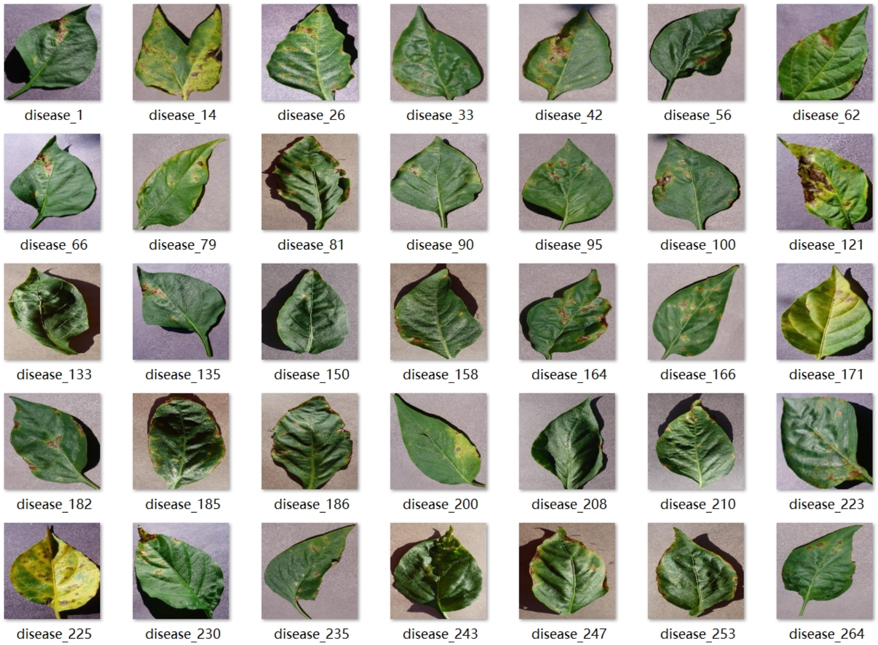




Case #3: Plant species classification

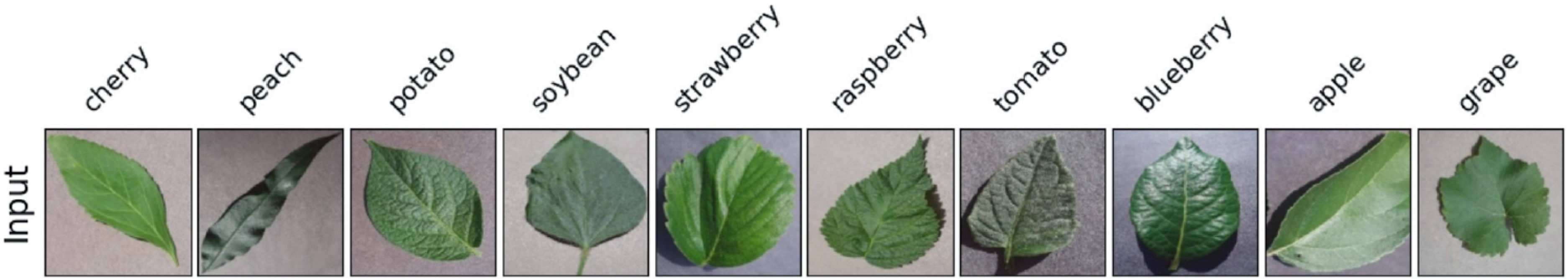
- Research data
  - Open-source PlantVillage dataset (https://github.com/spMohanty/PlantVillage-Dataset)





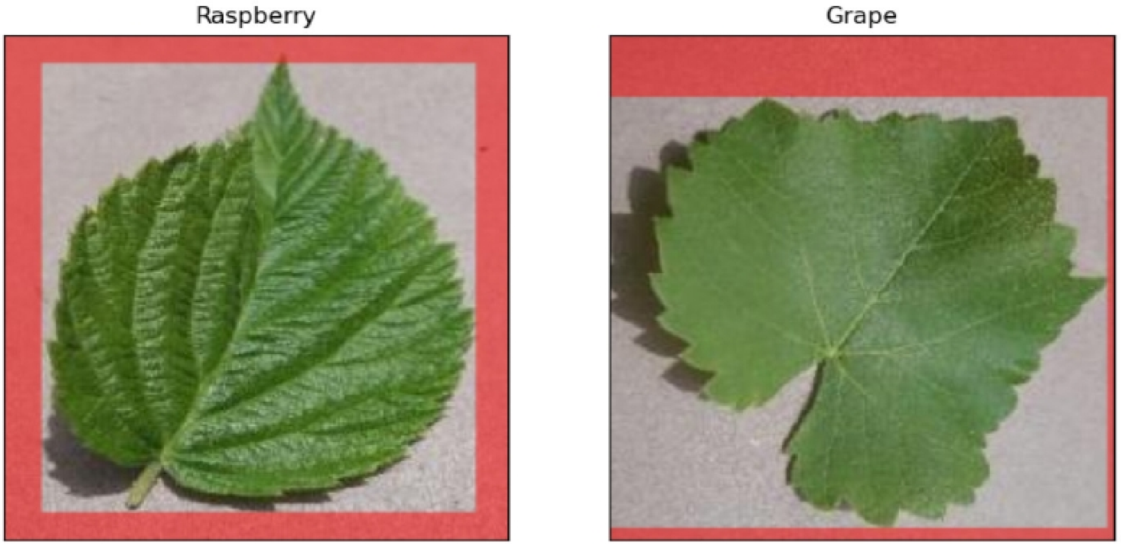
Case #3: Plant species classification

- Task and model
  - Multiclass classification: 10 species, include cherry, peach, potato, soybean, strawberry, raspberry, tomato, blueberry, apple, and grape
  - Model: AlexNet
  - Performance: 87.8% in test data (304 samples)



Case #3: Plant species classification

- XAI and FUL methods
  - Grad-CAM: get the model decisions
  - RRR: introduce expertise by the pre-set annotation matrix



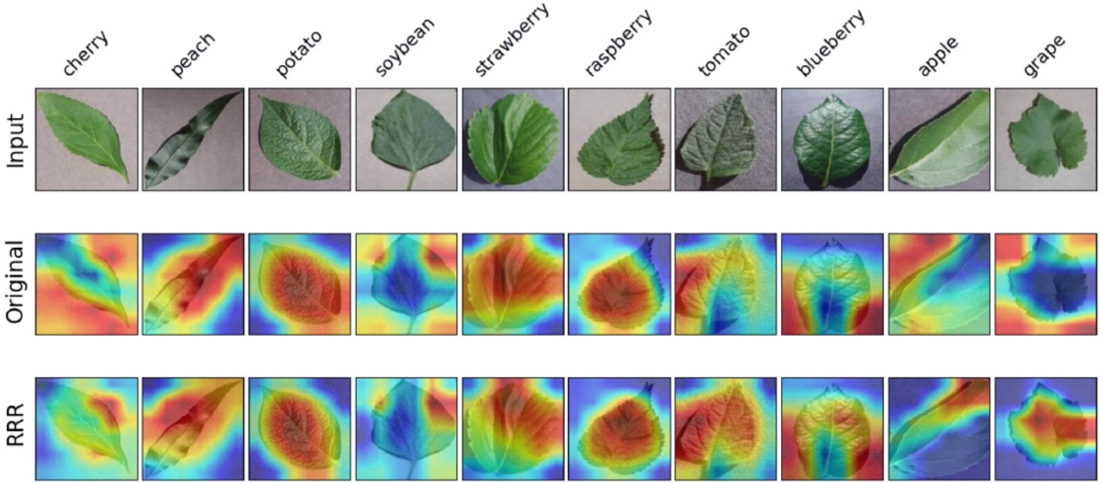
Case #3: Plant species classification

- Comparison of model accuracy and explanations

TABLE 3 | Accuracy and explanation assessment for the task of classifying plant species.

Models	Accuracy (%)	RMSE	CosineS	PIP		
				1%	5%	10%
Original	87.8	0.563	0.797	81.1	82.6	83.6
RRR	**92.4**	**0.550**	**0.810**	**86.1**	**87.3**	**87.3**

PIP is calculated based on three certain percents: 1, 5, and 10%.
The better results of every index are in bold.



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