ForestMonkey: Toolkit for Reasoning with AI-based Defect Detection and Classification Models

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***Abstract*—*Artificial intelligence (AI)* reasoning and *explainable AI (XAI)* tasks have gained popularity recently, enabling users to explain the predictions or decision processes of AI models. This paper introduces *forest monkey (FM)*, a toolkit designed to reason the outputs of any AI-based defect detection and/or classification model with data explainability. Implemented as a Python package, FM takes input in the form of dataset folder paths (including original images, ground truth labels, and predicted labels) and provides a set of charts and a text file to illustrate the reasoning results and suggest possible improvements. The FM toolkit consists of processes such as feature extraction from predictions to reasoning targets, feature extraction from images to *defect characteristics*, and a decision tree-based AI-Reasoner. Additionally, this paper investigates the time performance of the FM toolkit when applied to four AI models with different datasets. Lastly, a tutorial is provided to guide users in performing reasoning tasks using the FM toolkit.**

***Index Terms*—Morphological analysis, AI-Reasoner, defect characteristics, explainable AI.**

I. Introduction

There is an increasing number of *artificial intelligence (AI)* applications that recognise and classify objects for industrial use. The outputs of AI models need to be reasoned and explained to foster trust in the results among industries and enable researchers to improve AI algorithms. *Explainable AI (XAI)* techniques offer solutions for explaining and reasoning about AI models, leading to the development of various XAI toolkits. One such toolkit is XAI360 [1], published by Arya *et al.* of the *International Business Machines Corporation* in 2020, which integrates 14 diverse XAI methods.

In 2023, Ali *et al.* conducted a survey on a set of XAI techniques [2] and proposed four XAI taxonomies: scoop-based, model-based, complexity-based, and methodology-based, along with their corresponding use cases. Scoop-based XAI techniques, also known as data explainability methods [3]–[5], analyse the features extracted from the data to establish the relationship between the input and output of the AI model. Model-based XAI techniques, such as model explainability methods [6]–[8], break down the AI model into steps and provide explanations for each step. Complexity-based XAI techniques, such as intrinsic interpretable models (e.g. decision trees, bayesian models, linear models, and k-nearest neighbours), offer explanations with varying levels of detail based on the model's complexity. Methodology-based XAI techniques, referred to as post-hoc explainability methods [9]–[11], interpret the AI models by analyzing the model's backpropagation routes or perturbation signals. Zhang *et al.* [12] developed an AI reasoning framework that enables reasoning capabilities for the outputs of an AI-based detection and/or classification model. The framework incorporates a proposed feature extraction method known as *defect characteristics (DefChars)* and an ensemble *decision tree (DT)*.

In this paper, a toolkit named forest monkey (FM) is introduced, which implements Zhang *et al.* 's [12] framework using the Python programming language. The primary objective of the *FM* toolkit is to provide reasoning functionality for predictions made by an AI-based detection and/or classification model. The FM toolkit takes as input images, ground truth labels, and predicted labels from the AI model. Subsequently, the toolkit converts the predicted labels into reasoning target vectors and transforms the images into a DefChars matrix. Then, the toolkit generates the AI reasoning results, which include a set of charts and text-based improvement suggestions. By examining the reasoning results, users can gain a deeper understanding of their dataset and make improvements to their AI model.

In this paper, Section II provides an overview of the structure of the FM toolkit. Section III explains the implementation details of the toolkit. Section IV applies the toolkit to four different AI-based models using diverse datasets and discusses the performance in terms of execution time. Finally, Section V presents a tutorial on using the toolkit and provides an explanation of the generated output.

II. Toolkit Overview

This section provides an overview of the FM toolkit. The FM toolkit is developed to a Python-based package library. Figure 1 illustrates the architecture overview of the FM toolkit. Zhang *et al.*'s [12] AI-Reasoner serves as the foundation for the FM toolkit, which is a post-hoc and model-agnostic framework with data explainability. As a result, the toolkit only requires input images, ground truth labels and predicted labels from the AI model. The outputs of the toolkit are a

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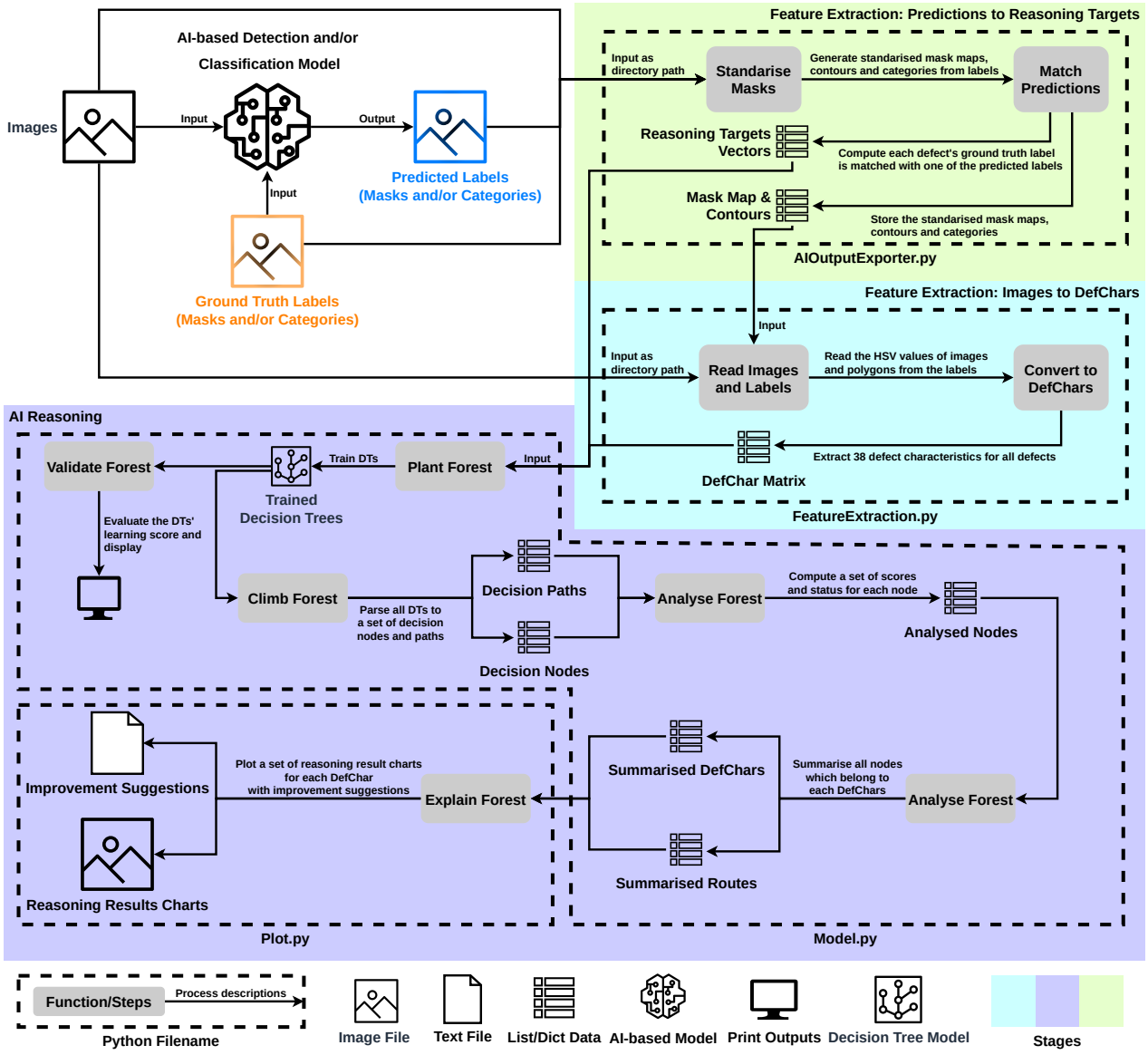


Fig. 1. FM toolkit structure overview.

set of charts and text-based improvement suggestions, which are stored as *png* and *txt* formatted files, respectively. The FM toolkit comprises three stages to perform an AI reasoning task:

- Feature extraction from predictions to reasoning targets: This stage converts all predictions into a set of reasoning target vectors based on the AI model's prediction tasks, such as detection, classification, or joint detection and classification. The reasoning targets include labels such as "detected," "undetected," "correctly classified," and "misclassified." Additionally, this stage standardises the mask-based labels to maintain consistent mask maps and contours of the defect regions.
- Feature extraction from images to DefChars: In this stage, all defect images are processed to generate a DefChar matrix. This is achieved by reading and processing the hue, saturation, and brightness (HSV) values and mask maps of the images.
- AI reasoning stage: This stage takes the DefChar matrix and reasoning target vectors as input to analyse the importance of each DefChar in causing correct or incorrect predictions by the AI model. It involves several steps, including *plant forest*, *validate forest*, *climb forest*, *analyse forest*, *summarize forest*, and *explain forest*. Finally, this stage produces improvement suggestions in the form of textual output and reasoning result charts for users to review.

III. Implementation

The FM toolkit is implemented using various packages, including *scikit-learn* [13], *OpenCV* [14], *NumPy* [15], *tqdm* [16], *matplotlib* [17], *shapely*, *pillow*, and *polygenerator*.

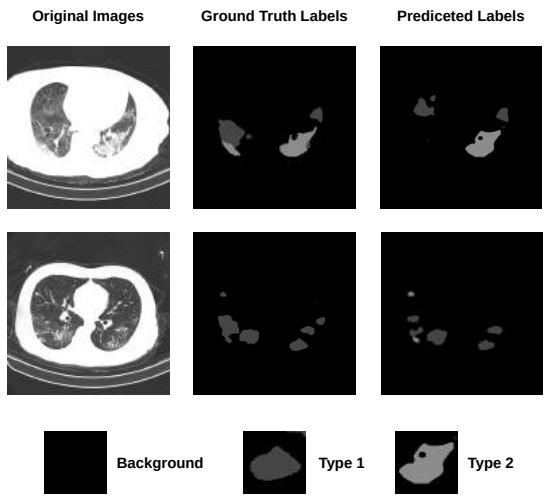


Fig. 2. Example of input data for FM toolkit, the real values in the highlighted area are the categories of defects $C \in \{1, 2 \dots\}$.

- *NumPy* is used for processing array-based and matrix-based data.
- *OpenCV* and *pillow* are utilised for image data processing, including computing the mask map and contours.
- *Shapely* and *polygenerator* are employed for converting polygon contours into shape-based DefChars.
- *scikit-learn* incorporates the DT model implementation, which is utilised for the AI reasoning functionalities.
- *matplotlib* is used for generating the reasoning result charts.

A. Data Preparation

An AI model is capable of detecting and/or classifying defects present in images. For this purpose, a classic dataset is utilised, which consists of pre-processed images and corresponding mask-based ground truth labels (stored in *png* format). Once the detection and/or classification tasks are performed by the AI model, its prediction results need to be converted into mask-based labels, mirroring the format of the ground truth labels. Figure 2 provides an example of the input data structure. The images, ground truth labels and predicted labels should be stored in three separate folders.

B. Feature Extraction: Predictions to Reasoning Targets

```
def process_dir(imgs_path,gt_masks_path,
predicted_masks_path,contain_type,only_type):
    ...
    return label_data={"mask map":[...],
           "contours":[...],
           "reasoning_targets":{...}}
```

The "Feature extraction from predictions to reasoning targets" stage involves the extraction of reasoning target vectors from AI predictions, as well as the mask map and contours from the ground truth labels. This can be accomplished by calling the *process_dir()* function; the required inputs for this function are:

- The path to the images folder.
- The path to the ground truth labels folder.
- The path to the predicted labels folder.

Additionally, two Boolean values, *contained_type* and *only_type*, are required to specify the extraction of reasoning target vectors for different tasks, such as a detection task (*contained_type* = *False*, *only_type* = *False*), a classification task (*contained_type* = *True*, *only_type* = *True*), or a joint detection and classification task (*contained_type* = *True*, *only_type* = *True*). The output of the function is a dictionary that contains the mask maps, contours, and reasoning target vectors for all ground truth defects.

C. Feature Extraction: Images to DefChars

```
def checkImage(imgs_path):
    ...
def readLabel(label_dict):
    ...
def loadData():
    ...
def featureExtract():
    ...
    return defchar={"defect_1":{...},
                    "defect_2":{...},...}
```

The "Feature extraction from images to DefChars" stage involves a sequence of four functions: *checkImage()*, *readLabel()*, *loadData()*, and *featureExtract()*. The *checkImage()* function is responsible for loading the images, while the *readLabel()* function loads the labels, which include mask maps and contours. The *loadData()* function reads the images and labels and creates a dictionary with basic information about the images and labels. The *featureExtract()* function is utilised to extract the DefChars and stores them in the dictionary. These functions are called in order to extract the DefChars from the images.

D. Pre-processing before AI Reasoning

```
def convert2List(defchar,feature_list,
label_dict):
    ...
    return id_list=[defect_id,...],
           feature_list,
           data=[[defchar 1],[defchar 2],...],
           targets={"detected":[...],
                    "undetected":[...],...}
def load_feature_data(data):
    ...
def load_target_data(targets,target_name):
    ...
```

In this section, there are three utility functions (i.e. *convert2List()*, *load_feature_data()*, and *load_target_data()*) implemented in the *Model.py* file. The *convert2List()* function returns several array-based lists derived from the feature extraction stage, including an id list, a feature list, a DefChars matrix and reasoning target vectors. The *load_feature_data()*, and *load_target_data()* functions are utilised to correspondingly load and prepare the feature and reasoning target data

for the AI-Reasoner model. These functions are responsible for converting the dictionary-based data into array-based data and loading it into the AI-Reasoner model.

E. Plant Forest

```
def plant_forest(n_tree=200):
    ...
    return model=[DT_1,DT_2,...]
```

The *plant_forest()* function is responsible for building and training multiple DT models using the loaded data. The function allows for an optional input to specify the desired number of DT models, which determines the number of decision rules generated. By invoking the *plant_forest()* function, the DT models are constructed and trained using the loaded data.

F. Validate Forest

```
def val_forest(model, feature_list):
    ...
    return good_learned=bool(),
           eval_=[learning_score, TPR, TNR],
           error_feature=[...]
```

The *val_forest()* function is responsible for evaluating the learning capability of the AI-Reasoner. It computes the overall learning scores, including true positive rate (TPR) and true negative rate (TNR), by averaging the learning scores of each trained DT model. Additionally, the function provides a set of DefChars that these DefChar made the incorrect decision rules during the reasoning task.

G. Climb Forest

```
def climb_forest(model,feature_list):
    ...
    return path=[...],node=[...],route=[...]
```

The *climb_forest()* function is responsible for parsing all decision nodes and paths from the trained DT models. It stores the parsed information in three lists: decision paths, routes, and decision nodes. Additionally, the list of DefChars names is required for the parsing process; the list can be accessed by calling *FeatureExtraction.feature_list*.

H. Analyse Forest

```
def analyse_forest(path,node,error):
    ...
    return analysed_node=[...]
```

The *analyse_forest()* function takes the parsed decision nodes and paths as input. It then computes a set of values for each node, which helps analyse the importance of the node in reasoning the AI predictions. The function outputs a list that extends the input node list with the computed values; this extended list provides additional information and insights about each node, allowing for a more in-depth analysis of the reasoning process.

I. Summarise Forest

```
def summary_forest(analysed_node,feature_list,
route,feature_range):
    ...
    return summary={"defchar 1":{...},...},
           route_to_1=[...],
           route_to_0=[...]
```

The *summary_forest()* function computes the importance for each DefChar to reflect the importance of each DefChar in influencing the AI predictions. It takes several inputs, including the analysed nodes list, parsed route, DefChars list, and value ranges. The function outputs a dictionary that contains the computed scores for each DefChar to provide a comprehensive overview of the importance of each DefChar.

J. Explain Forest

```
def explain_forest(report,feature_list,
save_path,route_plot=None):
    ...
```

The *explain_forest()* function is responsible for generating a set of visualised reasoning result charts and providing improvement suggestions based on the summarised overviews from the previous stage. The input includes the generated dictionary from *summary_forest()* function, DefChars name list and folder path where the reasoning results will be saved. Furthermore, a set of important decision routes can be optionally plotted by setting *route_plot* as true. The reasoning result charts are saved in the *png* format, while the improvement suggestions are stored in a *txt* format file.

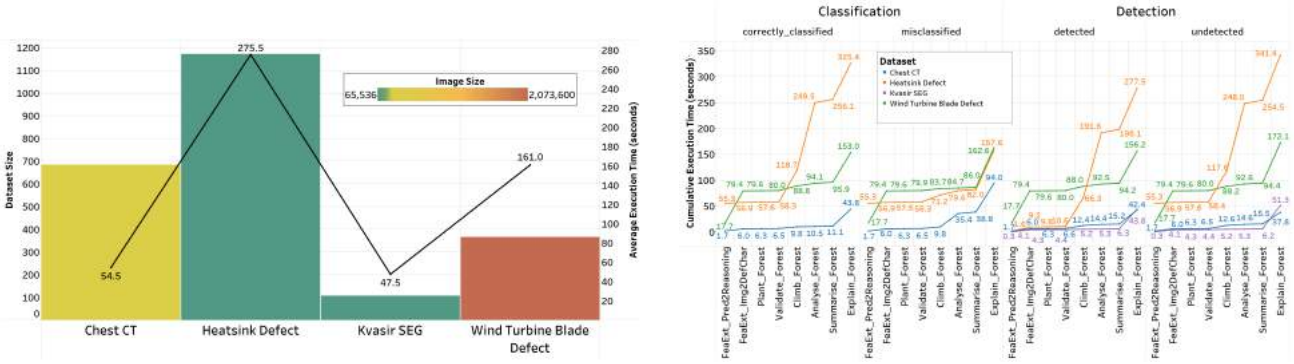
IV. Performance

In this section, the FM toolkit was applied to four different AI-based defect detection and classification models using different datasets. The models include a *COVID-CT-mask-net (CCMN)* trained on chest CT images dataset [18], a *lightweight fully convolutional network (LFCN)* trained on heatsink defect images dataset [19], a *deep residual U-Net++ (ResUNet++)* trained on Kvasir-SEG dataset [20], and an image-enhanced mask R-CNN (IE-MRCNN) trained on wind turbine blade defect image dataset [21]. Table I presents the defect distributions of these four datasets, providing an overview of the reasoning targets and quantities of defects present in each dataset. Additionally, the running time in each step of the FM toolkit was recorded to analyse its performance. This allows for an assessment of the toolkit's efficiency and provides insights into potential areas for improvement.

Figure 3a illustrates the execution times when applying the FM toolkit to different datasets. It shows that the execution time is positively correlated with the dataset size and image size, indicating that larger datasets or images require longer execution times. Figure 3b illustrates the stacked execution times of each stage for different reasoning targets. Among the various stages of the FM toolkit, *feature extraction from images to DefChars*, *climb forest*, *analyse forest*, and *explain*

TABLE I
INFORMATION OF FOUR DATASETS; WHERE N/A REPRESENTS NO SUCH TASKS.

Dataset	Image Size	Number of Defects for Each Reasoning Targets (percentage)				Total
		detected	undetected	correctly classified	misclassified	
Chest CT	512×512	244	147	215	29	391
Heatsink Defect	256×256	804	368	774	30	1172
Kvasir-SEG	256×256	104	3	N/A	N/A	107
Wind Turbine Blade Defect	1920×1080	311	55	296	15	366



(a) Average execution time of the FM toolkit for different datasets. The black dots represent the average execution time, indicated on the right axis. The bars represent the dataset size, indicated on the left axis, and the colours of the bars correspond to the dataset's image size, as shown in the legends.

(b) Stacked execution time of each stage in the FM toolkit for different reasoning targets.

Fig. 3. Execution time of FM toolkit.

forest consumed relatively more time compared to other stages. In summary, the FM toolkit can complete a reasoning task in at least 40 seconds. However, the execution time may increase when dealing with datasets containing large amounts or large-size images.

V. TUTORIAL

This section describes a tutorial for applying the FM toolkit to reason the outputs of an AI model. Users can follow the Python programming code below to run the FM toolkit. The code can be written in a single Python file or a notebook.

Step 1: Import the FM toolkit.

```
from AIReasoner import AIOutputExporter
from AIReasoner import FeatureExtraction
from AIReasoner import Model
from AIReasoner import Plot
```

Step 2: Set the directory paths of original images, ground truth labels and predicted labels from the AI model; the related data preparation is described in Section III-A.

```
images="/path/.../"
gt_labels="/path/.../"
predicted_labels="/path/.../"
```

Step 3: Feature extraction from prediction to reasoning targets

```
contain_type=True
type_only=False
label_data=AIOutputExporter.process_bydir(
           images,gt_labels,predicted_labels)
```

Step 4: Feature extraction from images to DefChars

```
FeatureExtraction.checkImages(images)
FeatureExtraction.readLabel(label_data)
FeatureExtraction.loadData()
defchar=FeatureExtraction.featureExtract()
```

Step 5: Pre-processing before reasoning task

```
feature_list = FeatureExtraction.feature_list
id_list,feature,data,target=Model.convert2List
(defchar,feature_list,label_data)
Model.load_feature_data(data)
```

Step 6: Execute AI reasoning task for all reasoning targets

```
for t in target.keys():
    Model.load_target_data(target[t],t)
    model = Model.plant_forest()
    tree_validated,scores,errors=Model.
val_forest(model,feature)
    path,node,route=Model.climb_forest(model,
feature_name=feature)
    analysed_node=Model.analyse_forest(path,
node,error)
    report,route_t,route_nt=Model.
summary_forest(analysed_node,route,feature,
```

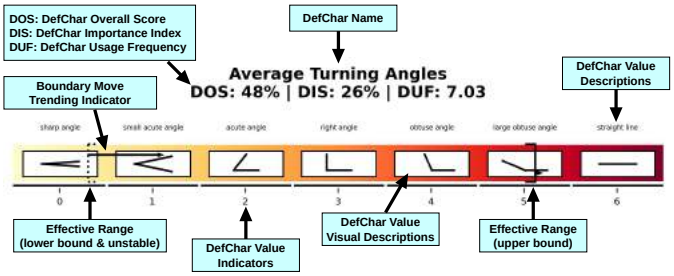


Fig. 4. FM toolkit example output with element descriptions.

```
FeatureExtraction.get_FeatureRange())
    Plot.explain_forest(report,feature,
"/directory/path/to/save/"+t)
```

After completing these six steps, the reasoning results will be saved in the specified directory. Figure 4 illustrates an example of a reasoning result chart generated by the FM toolkit. The chart provides an explanation for each element in the chart, allowing users to understand the significance of each DC and its value range in influencing the AI model's correct or incorrect predictions in detection and/or classification tasks. Additionally, users can refer to the *improvement_recommendations.txt* file for improvement suggestions on how to enhance their dataset and model based on the reasoning results.

VI. Conclusion

This paper presents the integration of Zhang et al.'s AI-Reasoner framework into a toolkit called FM, implemented in Python. The FM toolkit can be easily used by importing it as a Python package, and a detailed tutorial is provided to guide users in utilising the toolkit effectively. Furthermore, the FM toolkit is evaluated by applying it to four different AI-based models with diverse datasets to assess its execution performance.

In terms of future work, several enhancements are suggested for the FM toolkit. Firstly, the implementation of GPU-enabled parallel computations could be explored to accelerate the execution speed. Additionally, the development of interactive interfaces would enhance user experience and make the toolkit more user-friendly. Furthermore, visualisations of the DefChars could be incorporated to provide users with a better understanding of the reasoning process.

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