Black-box error diagnosis in deep neural networks: a survey of tools
Piero Fraternali*, Federico Milani†, Rocio Nahime Torres‡, Niccolò Zangrando§
Politecnico di Milano
Piazza Leonardo 32, Milan, Italy
{ *piero.fraternali, †federico.milani, ‡rocionahime.torres, §niccolo.zangrando}@polimi.it

Abstract—The application of Deep Neural Networks (DNNs) to a broad variety of tasks demands methods for coping with the complex and opaque nature of these architectures. The analysis of performance can be pursued in two ways. On one side, model interpretation techniques aim at “opening the box” to assess the relationship between the input, the inner layers and the output. For example saliency and attention models exploit knowledge of the architecture to capture the essential regions of the input that have most impact on the inference process and output. On the other hand, models can be analysed as “black boxes”, e.g., by associating the input samples with extra annotations that do not contribute to model training but can be exploited for characterizing the model response. Such performance-driven meta-annotations enable the detailed characterization of performance metrics and errors and help scientists identify the features of the input responsible of prediction failures and focus their model improvement efforts. This paper presents a structured survey of the tools that support the “black box” analysis of DNNs and discusses the gaps in the current proposals and the relevant future directions in this research field.

Index Terms—black-box, error diagnosis, machine learning, evaluation, metrics

I. INTRODUCTION
The application of Deep Neural Networks (DNNs) to a broad variety of tasks demands methods for coping with the complex and opaque nature of these architectures. Such systems are normally used and evaluated as black-boxes: the quality of their output is validated either qualitatively via manual inspection or quantitatively by comparison with ground truth test data. Quantitative performance analysis exploits standard metrics, such as Accuracy, Precision, Recall, F1-Score, or Average Precision, which are implemented off-the-shelf in most DNN frameworks. Selecting the most appropriate metrics for quantitative performance analysis is by itself a concern that requires attention. Several works [1]–[4] discuss the challenges and the best practices relevant to the use of performance evaluation metrics both in general and for specific tasks. Standard metrics enable and end-to-end assessment of a model without providing any information on the potential sources of failures and on the components of the model that may cause them. Hence the difficulty of identifying flaws in the architecture and of implementing appropriate countermeasures arises. Two approaches can be pursued to study model behavior. One line of research aims at improving model interpretability, by characterizing the relation of the internal representations of deep models to the input and output [5]–[8]. Techniques such as the Class Activation Maps (CAMs) [9]–[13] highlight the most influential regions of the feature maps at different network levels and enable better insight into the model behavior.

An alternative option is to consider the model as a black box and analyze the impact that the properties of the input have on performances. The methods of this category enrich the description of the input samples with additional attributes not used for training and study how the performance metrics depend on the value of such attributes and how errors (e.g., wrong classifications or detections) correlate to specific features of the input. Such diagnosis-oriented input attributes can be either obtained automatically (e.g., image color space and aspect ratio, text language, etc.) or provided manually (e.g., domain-specific meta-data). A black-box performance analysis and error diagnosis tool can be used to address questions such as: “Does the model fail consistently when the inputs exhibit a specific characteristic?” “How much would a given performance metrics improve if a particular type of error is removed?” The insight resulting from black-box diagnosis can help model designers improve the training data set and/or focus the DNN design on the improvements with the highest expected gain.

A. Focus of the Survey and Methodology
The focus of this paper is a survey of the tools that support the black-box diagnosis of DNNs. The target of the research comprises those methods that exploit only knowledge about the input and output. Among such works, we highlight the proposals that provide a tool for DNN design, training and evaluation. This perimeter excludes contributions that also address DNN behavior and performances but pursue different targets such as special-purpose and domain-dependent evaluation metrics, the visualization of DNN internal representations, model design for interpretability, and human-in-the-loop interpretation.

The corpus of the relevant research has been identified by means of the following procedure:

1) A keyword search has been conducted in the major bibliographic sources (Google, Google Scholar, DBPL, ACM Digital Library) using key phrases composed as follows:
<search> :- <task> + <goal> + <system>
The surveyed diagnosis tools span the following tasks:

- Classification (CL): assignment of class labels to domain objects. Samples can belong to any media: text, visual or aural content, graph and record data.
- Object Detection (OD): localization of objects of a certain class through bounding boxes in images and videos.
- Semantic Segmentation (SS): assignment of a class label to each pixel in images or videos.
- Instance Segmentation (IS): similar to semantic segmentation but multiple objects of the same class are treated as separate instances.
- Object Tracking (OT): similar to object detection but each unique object is tracked as it moves across the frames of a video.
- Pose Estimation (PE): recognition of single or multiple body poses through key points in image and video.
- Action Detection (AD): assignment of an action label to a video.
- Video Relation Detection (VRD): performs the spatio-temporal localization of object and subject pairs in videos and assignment of a label that describes their interaction.

2) Media types: Depending on the task several media types can be relevant. The media types processed by the surveyed tools comprise image, text, video and graph data. The “generic” media type is used to refer to values of arbitrary record type.

3) Metrics: The quantitative analysis relies on metrics that may vary based on the targeted task. Near 50 metrics are mentioned in the surveyed tools. For the definition of the non standard metrics, the reader is referred to the references provided in the comparison tables.

4) Special functions: In addition to the computation of the performance and behavioral metrics, some tools implement other functions that improve the characterization of the input or of the output and the presentation of results.

- Overall / Per-class / Per-property performance analysis: the tool supports the computation of the metrics for the entire data set and/or for individual classes or properties of the input.
- Overall / Per-class / Per-property report: the tool supports the construction of summary reports for the different levels of granularity used to compute the metrics.
- Categorization of errors: the tool supports the grouping of metrics and errors into task specific categories, e.g., confusion with similar/dissimilar classes, poor localization, occlusion, etc.
- Error contribution isolation: the tool supports error impact analysis by highlighting the effect of all errors of a certain type in the computation of the performance metrics.
- Properties / Class distribution: the tool supports the visualization of the distributions of properties or of classes in the input data set.

5) Custom property editing: Some tools integrate a framework for adding custom properties to the input samples, with the following features:

- Annotation purpose selection: annotation can be distinguished into those for training (e.g., class labels) and those for diagnosis (e.g., custom properties).
- Manual annotation creation: a graphical interface allows the user to add annotations to the input samples.
- Automatic annotation extraction: the framework enables the execution of algorithms for extracting meta-data and associating them to the input samples as custom properties.
- Annotation visualization: the input data set and its annotations can be inspected with different criteria (e.g., all samples of a certain class or with a specific property).

6) Openness and extensibility: Openness and extensibility are fundamental properties to support adoption especially when novel metrics or diagnosis approaches are proposed. The surveyed tools have been assessed based on their open source status and on the effort required for their extension.

The reviewed proposals are categorized and compared based on several aspects: the machine learning task they support, the metrics they define and implement, and the extra annotations of the input they exploit. A connection is established with complementary methods and the most relevant open issues and research directions are discussed.

The rest of the paper is organized as follows: Section II describes the dimensions used to categorize the surveyed tools, Section III and IV describes and compares the different tools based on the identified dimensions; Section V highlights the open issues and proposes possible research directions; finally, Section VI draws the conclusions.

II. CLASSIFICATION OF THE DIAGNOSTIC TOOLS

To characterize the state-of-the-art the relevant proposals are described and compared along six dimensions: task, media types, metrics, special functions, custom properties, and openness and extensibility.

1) Task: An error diagnosis tool is typically designed for performance analysis of a specific task, which in turn may apply to a specific media type or to a range of media types. The surveyed diagnosis tools span the following tasks:

- Classification (CL): assignment of class labels to domain objects. Samples can belong to any media: text, visual or aural content, graph and record data.
- Object Detection (OD): localization of objects of a certain class through bounding boxes in images and videos.
- Semantic Segmentation (SS): assignment of a class label to each pixel in images or videos.
- Instance Segmentation (IS): similar to semantic segmentation but multiple objects of the same class are treated as separate instances.
- Object Tracking (OT): similar to object detection but each unique object is tracked as it moves across the frames of a video.
- Pose Estimation (PE): recognition of single or multiple body poses through key points in image and video.
TABLE I
THE SURVEYED TOOLS LISTED BY ASCENDING YEAR OF PUBLICATION. IN THE CODE COLUMN, “-” INDICATES THAT THE CODE IS NOT AVAILABLE AND “LINK” CONTAINS A REFERENCE TO THE CODE REPOSITORY

| Reference                  | Year | Task | Media | Data set independence | Code |
|---------------------------|------|------|-------|-----------------------|------|
| Dollar et al. [14]        | 2009 | OD   | image | no                    | -    |
| Hoiem et al. [15]         | 2012 | OD   | image | yes                   | link |
| Russakovsky et al. [16]   | 2013 | OD   | image | no                    | -    |
| COCO API [17]             | 2014 | OD,  | image | yes                   | link |
| Hariharan et al. [18]     | 2014 | IS   | image | no                    | -    |
| Zhu et al. [19]           | 2015 | OD   | image | no                    | -    |
| ModelTracker [20]         | 2015 | CL   | generic | yes               | -    |
| Redondo et al. [21]       | 2016 | PE,  | image | no                    | link |
| Prospector [22]           | 2016 | CL   | generic | yes               | -    |
| Zhang et al. [23]         | 2016 | OD   | image | no                    | -    |
| Ronchi et al. [24]        | 2017 | PE   | image | yes                   | link |
| Explanation Explorer [25] | 2017 | CL   | generic | yes               | link |
| Squares [26]              | 2017 | CL   | generic | yes               | -    |
| Sigurdsson et al. [27]    | 2017 | AD   | video | no                    | link |
| DETAD [28]                | 2018 | AD   | video | yes                   | link |
| Nekrasov et al. [29]      | 2018 | SS   | image | no                    | -    |
| Manifold [30]             | 2018 | CL   | generic | yes               | link |
| What If Tool [31]         | 2019 | CL,  | generic | yes               | link |
| TIDE [32]                 | 2020 | OD,  | image | yes                   | link |
| ODIN [33]                 | 2020 | OD,  | image | yes                   | link |
| Padilla et al. [34]       | 2020 | OD   | image | yes                   | link |
| TF-GrAF [34]              | 2020 | OD   | image | yes                   | link |
| Boxer [35]                | 2020 | CL   | generic | yes               | -    |
| OpenVINO [36]             | 2020 | CL,  | images | yes               | -    |
| GNNVis [37]               | 2020 | CL   | graph  | yes                   | -    |
| Padilla et al. [38]       | 2021 | OD,  | image | yes                   | link |
| TracKlinic [39]           | 2021 | OT   | video  | yes                   | -    |
| Chen et al. [40]          | 2021 | VRD  | video  | yes                   | link |

This qualitative dimension is characterized by means of the following values:

- Open source: the code is public and freely available.
- User-defined properties: the tool enables the plug-in of custom analysis of user-defined properties not present in the original proposal.
- User-defined metrics: the tool can be extended with custom metrics without modifying the framework.
- Data set independence: the tool can be applied to the processing of multiple data sets.

III. TOOL DESCRIPTION

Table I lists the 28 identified tools with the name of the tool or of its authors, the publication year, the targeted tasks, the relevant media types, the ability to work with different data sets, and the link to the source code (only for open-source tools[1]). As shown in Figure 1, the most common tasks are Objection Detection and Classification. Most tools work with images or with generic inputs, provide open-source code and have been released in the last three years. In the rest of this section we provide a brief description of the proposals in ascending chronological order.

1) Dollar et al.: The authors in [14] present a new data set for pedestrian detection, which consists of an annotated video with challenging low resolution images and occluded people. The data set is used to evaluate several detectors and the idea of exploiting ad-hoc features of the input to help diagnose error and support design improvement is introduced. To this end, performances are broken down based on specific properties of the input, such as the scale, the aspect ratio of the ground truth bounding boxes and the presence of occlusions of the pedestrians. Although the code was not released, this was a first introduction to the analysis of performance based on the observations properties.

2) Hoiem et al.: The work in [15] pioneered the systematic black-box approach to error analysis in object detection tasks and showed the utility of adding extra annotations to the input besides the labels needed for training. The framework exploits a fixed set of diagnosis-oriented object meta-data that can affect the model accuracy, such as: size, parts visibility, aspect ratio, shape and occlusion. The authors demonstrate how breaking down standard metrics into sub-metrics linked to a metadata value aids in understanding model faults and in focusing redesign where the margin for improvement is maximal.

3) Russakovsky et al.: The work in [16] follows the black-box diagnosis method of [15] and assesses the performance of several object detectors on the ImageNet Large Scale Visual Recognition Challenge (ILSVRC) data set. The first analysis breaks down the performance indicators by per-image properties, such as the number of instances per image or the chance performance of localization (CPL). A second analysis shows how the performances are affected by per-class properties, such as the distinctiveness of color, the distinctiveness of

1The link to the code repository is navigable in the online version of the paper.
shape, the deformability within an instance and the amount of texture.

4) **COCO API:** A step towards the popularization of input properties as an aid for error diagnosis is found in the development framework of the MS COCO data set [17]. The computation of mAP is differentiated based on object size: mAP_{small}, mAP_{medium} and mAP_{big}. This distinction enables a better diagnosis of issues and the design of strategies to increase localization capabilities, such as multi-scale object detection [41]. In addition to the metrics break down, the API also allows developers to load any data set that respects the MS COCO format and to visualize both the images and the annotations.

5) **Hariharan et al.:** The work in [18] introduces simultaneous detection and segmentation (SDS) as a novel computer vision task. The authors provide the DNN architecture and a tool for its diagnosis. Besides the assessment of standard metrics, error diagnosis is supported by introducing three error classes (localization, confusion with similar classes, and confusion with background) and by computing the impact of each error type on the performance metrics.

6) **Zhu et al.:** The authors of [19] follow the methodology of [15] and evaluate object detectors using custom properties. They compare different methods for creating object proposals for the PASCAL VOC data set using different object characteristics: size, aspect ratio, iconic view, color contrast, shape regularity and texture. Even if the focus is on the detection results, the paper also illustrates how to investigate model limitations exploiting objects properties, with the novelty of applying such analysis to the creation of object proposals. The described analysis exposed the sensitivity of the model to the objects characteristics.

7) **ModelTracker:** The work in [20] applies to the study of a classifier a different black-box approach that combines metrics summaries and novel interactive visualizations. Binary predictions are color-coded and arranged by classification score. The analysis of results is facilitated by tagging input samples with custom properties and by highlighting samples similarity and outliers.

8) **Redondo et al.:** The authors of [21] propose a diagnostic tool tailored to the study of pose estimation errors. The tool examines the effects of fixed object properties (such as aspect ratio, size, visibility of parts) on the detection and pose estimation performances and enables the study of the impact of different types of pose-related False Positives. The authors analyze four state-of-the-art object detection and posture estimation models to uncover flaws and recommend improvements.

9) **Prospec:** The work in [22] describes a web-based tool that implements a partial dependence technique for determining the impact of each input feature on the DNN results. The developer can apply changes to the input data and measure the impact on the output. The system suggests the shift in the value of each input feature that would lead to the greatest performance improvement. The effectiveness of the approach is demonstrated in a diabetes prediction task.

10) **Zhang et al.:** In [23] the authors apply error diagnosis to the state-of-the-art pedestrian detection methods. They enhance the annotations of the Caltech [14] data set and study both False Positives (FPs) and False Negatives (FNs) with different error categories: localization, background, and annotation for FPs and scale, viewpoint, occlusion, and others error types for FNs. The authors also analyze the impact of FPs on performances.

11) **Ronchi et al.:** The work in [24] applies the approach of [15] to the Multi-Instance Pose Estimation task. Three errors types are defined (localization, scoring and background) and the impact of three challenging factors is studied (occlusion, crowding and size). Their tool visualizes the distribution of errors for each key point and highlights the improvement in the Precision-Recall curve obtainable by correcting specific types of errors.

12) **Explanation Explorer:** In [25], the authors of Prospec [22] describe a novel tool for the assessment and interpretability of binary classifiers. Their approach comprises two steps: 1) explanation generation, which computes the features of the input samples that impact the outcome most significantly; 2) interactive visualization of the explanations. The visualization is organized in three stages: 1) outcome-level, focusing on the overall accuracy; 2) feature-level, presenting the computed explanations along with the corresponding features; and 3) instance-level, which allows the user to analyze each instance and derive hypotheses about the classifier failures. The authors advocate that visual analytics should play a major role in error diagnosis but also highlight that not all failures can be rectified by training a stronger model because some errors require bias mitigation in the original data set.

13) **Squares:** Squares [26] is a tool for the interactive performance analysis of multi-class single-label classifiers which supports the visualization of results for up to 20 classes at class and at instance level. The categories and the corresponding instances are displayed on the same row with a distinctive color. The observations are ordered by their prediction confidence score and grouped. The first group represents the FNs whereas the second cluster comprises both the TPs (highlighted with the color of their class) and the FPs (highlighted with the color of their true class). When an observation is selected from one class its representations in the other classes are emphasized visually, thus allowing a comparison among the different predictions of the same sample.

14) **Sigurdsson et al.:** The work in [27] surveys the state-of-the-art in the action detection task and analyzes the performances of the existing methods. The first assessment is based on the categorization of errors in four classes: boundary, other class with the same object, other class with the same verb, other class with neither and no class. A further analysis evaluates the models w.r.t. the complexity of the objects/verbs that characterize a category. Finally, the authors examine the impact of two specific features of the input: the temporal extent of the action and the presence of people.

15) **DETA:** The focus of [28] is on the identification of temporal actions in videos. The diagnosis tool enables the analysis of FPs and FNs and the estimation of the sensitivity of mAP-based metrics to six action characteristics: length, context distance, agreement, coverage, context size and number of instances.
16) Nekrasov et al.: in [29] the authors apply the black-box diagnostic strategy of [15] to the semantic segmentation task. However a public implementation of their toolkit is not provided. 

17) Manifold: The authors of [30] discuss an interactive framework for the evaluation and debugging of general machine learning models. An agreement analysis function enables the comparison of model pairs by highlighting the similarities and differences of their predictions. A feature distribution function permits the selection of a subset of the samples and provides a measure of the intra-group similarity based on the occurrence frequency of each feature.

18) What If Tool: As the name suggests, the tool described in [31] allows researchers to analyze the performances of machine learning systems in hypothetical situations by visualizing the effect of several features on different models and on different subsets of the input data. Among all the surveyed tools, this is the only one providing also a fairness analysis that highlights bias in the input data set. The offered functionalities include data point editing, counterfactual reasoning, performance measures for single- and multi-class classification and regression and data set fairness optimization.

19) TIDE: the tool illustrated in [32] supports error diagnosis in object detection and instance segmentation and is applicable to multiple data sets and output prediction formats. Similarly to [15] it focuses on the classification of detection and segmentation error types and on the provision of compact error summaries and of meaningful impact reports. For example, it includes the direct comparison of results by different models. Unlike other tools such as [15], [33]. TIDE purposely avoids resorting to properties of the input other than those used for training.

20) ODIN: The ODIN framework [33] aims at generalizing and integrating into a unique solution the previous approaches to DNN black-box diagnosis for classification, object detection and instance segmentation. ODIN allows the addition of custom properties to the input, supports the plug-in of user-defined performance indicators and implements a wide range of metrics and analysis reports off-the-shelf. It can be used to study both model performance and data set bias and combines error impact sensitivity and confidence calibration. The latter analysis evaluates the similarity of the distribution of predictions to the real probability distribution of the input data. The tool also features a GUI for input annotation and thus provides a one stop solution spanning all the phases from training set preparation to DNN assessment.

21) Padilla et al.: The authors of [4] discuss the most commonly used metrics for object detection and provide the implementation code in a toolkit. The work in [38] describes the most recent release, which makes the toolkit independent of the input formats, adds more bounding box formats, and includes novel spatio-temporal metrics for object detection in video.

22) TF-GraF: The goal of the work in [34] is to create an easy-to-use Tensorflow object detection environment, simplifying the installation and set-up and the coding and execution of the workflows. The tool supports pre-processing, training and evaluation with the standard MS COCO metrics. It incorporates the best known object detection and instance segmentation architectures (Faster RCNN, SSD, Mask RCNN) and provides the visualization of the training and test data sets. Non-experts can configure, train, and assess DNNs with no programming, which is a unique capability among all the reviewed tools.

23) Boxer: The work in [35] presents a tool called Boxer for comparing the performances of different classifiers. The system supports the selection of metrics, the grouping of training and test data into “boxes” based on selected features and the comparative visualization of outputs. To evaluate data quality and bias, a novel method based on set algebra is presented to link views and analyze multiple data subsets. The authors demonstrate the tool effectiveness in a variety of use cases. Even if the tool is not built to be scalable, various strategies for dealing with very large data sets are proposed.

24) OpenVINO DL Workbench: the work in [36] focuses on model training, analysis, optimization, evaluation and deployment, covering the entire model development workflow with a hybrid black-box and white-box approach. The proposed tool includes an Accuracy Checker that implements a black-box analysis for classification, regression, and object detection tasks by computing the most common metrics for the whole data set and per class. The tool also supports the white-box analysis, for example to evaluate and improve model performance in terms of execution time and memory consumption.

25) GNNVis: The work in [37] addresses the diagnosis of Graph Neural Networks [42]. The proposed approach investigates error patterns shared by groups of nodes so as to provide insights into the model performances. The tool includes multiple interactive visual analytics functions and graph-specific metrics, enabling the user to study the impact of different node features and relationships, such as node label consistency, node degree, and nearest training nodes.

26) TrackKlinic: The work in [39] studies the factors that challenge object tracking in videos. Custom properties can be manually associated with the video frames to specify seven common error-inducing factors: occlusion, rotation, out-of-view, background clutter, illumination variation, shape variation, and motion blur. The proposed diagnosis tool exploits the IoU base metrics to analyze the failure rates and the success scores of ten state-of-the-art architectures applied to three benchmark data sets manually annotated with the above mentioned factors. Per-frame proposals of alternative models can be visualized together and compared with the ground truth annotations. The diagnosis results show that most models fail when complex situations occur, such as out-of-view or shape variation.

27) Chen et al.: the work in [40] focuses on the relation detection task in videos and assesses the state-of-the-art detectors over two benchmark data sets (ImageNet-VidVRD [43] and VidOR [44]). The authors study the False Positives, by classifying them into different types and computing their impact over the Average Precision, the False Negatives, by analyzing their distribution across different input characteristics (e.g., the video length, the number of subject/predicate/object instances, the subject/object pixel scale) and the performance gain achievable by removing each error type.
Figure 2 illustrates the distribution over time of the surveyed works. If one does not consider the early 2009 work [14], the timeline shows that the interest in the black-box diagnostic tools for DNNs begun in 2012, the same year in which the research on Deep Learning started its escalation. The idea originated in the Computer Vision field for such tasks as object detection and image segmentation and then propagated to other Machine Learning applications.

IV. COMPARISON OF DIAGNOSTIC TOOLS

For each tool described in Section III the supported metrics and types of analysis were extracted, resulting in more than 70 options. For ease of comparison four tables are introduced, one for each family of homogeneous metrics/analyses: generic multi-task (Table II), classification (Table III), localization (Table IV), and a miscellaneous category grouping the functions found in the less frequent tools for graph analysis, object tracking, and pose estimation (Table V). The rows specify the metrics/analysis and the columns the tools that support them sorted in chronological order. For space reasons, the tool or authors’ names are omitted but they can be recovered from Table I. Each cell shows if the given option is offered by the specified tool: “yes” when it is implemented, “no” when it is not provided or “-” when it is not relevant for the specific tool. For example, a metrics specific for pose estimation is not relevant for tools focused on object tracking. Note that when some base metrics is used to compute a derived metrics (e.g., IoU and AP in Table IV) the table row of the base metrics contains the “yes” value only when the tool exposes the base metrics explicitly.

A. Multi-task metrics and analyses

Table II lists 16 general metrics that apply to all the considered tasks and the 22 tools that implement them. Only Accuracy is well represented in the surveyed classification tools. Other standard machine learning metrics (e.g., precision, recall, F1-score and AUCs) are present only in 3 or 4 tools, less than one may expect. A similar consideration also holds for the Precision-Recall, F1 and ROC curves, usually employed to visualize and compare performances and optimize the hyperparameters. Only 8 out of 21 tools offer such features. The most represented types of analysis are those related to False Positives and False Negatives, which are the most common starting points for error diagnosis.

B. Classification metrics and analyses

Table III lists 8 classification-specific metrics implemented in 7 frameworks. Most options are included in very few tools and several ones are implemented by only one proposal: ME, MAE, MSE, Odds Ratio and TN analysis.

C. Localization metrics and analyses

Table IV presents the 6 localization-specific metrics and the 19 tools that implement them. The surveyed frameworks support a variety of localization tasks: OD, IS, SS, AD and PE. The review shows that there is little consensus among localization-oriented frameworks about which metrics are essential and should be provided off-the-shelf. The implementation by tools concentrates only on the metrics commonly required by the most popular Computer Vision benchmarks: Average Precision (IoU) for OD and IS; other useful metrics both general and localization-specific such as Miss Rate, Average Recall (IoU) or F1 Score are implemented rather infrequently by the tools that focus on localization tasks.

D. Graph, Object Tracking and Pose Estimation metrics and analyses

Table V lists task-specific metrics found in tools designed for graph-based classification, OT and PE. Also in this case a lack of consensus about a common core set of relevant metrics can be observed. For example both [24] and [21] focus on PE but do not share any of the task-specific metrics.

E. Error categorization metrics and analyses

Table VI lists 12 tools that implement error categorization and define 14 types of errors. The categorization of errors was first proposed in [15] and then inspired more recent tools to introduce novel classes. From Table VI it is possible to observe that error categorization is provided only by OD, IS or PE tools and is not yet common for other tasks. As discussed in the surveyed works, error categorization unveils specific factors associated with model failure that are difficult to extract from aggregated metrics alone. Most tools that enable error categorization exploit this feature for error contribution analysis to highlight the performance gain obtainable by removing a specific type of error.

F. Additional features

Table VII presents 14 additional features not related to any specific metrics. Some functions (overall, per-property and per-class analysis/reporting, built-in/user-defined properties) refer to the possibility of inspecting the input or output at different levels of granularity. User-defined properties and metrics characterize the extensibility of tools. Class/property distribution qualifies the frameworks that enable the display.
of the input samples grouped by classes or by built-in or user-defined properties. The multi-level analysis and the comparison of models are present in most tools. Few frameworks allow the user to provide custom evaluation criteria. Most tools focus on evaluation and do not support the creation or enrichment of input data sets by means of an annotator for labeling samples and of a visualizer for inspecting data with user-defined queries. Such functions may ease the generation of a new data set from scratch and the addition of diagnosis-oriented attributes to an existing data set. Only 2 tools include an annotator GUI and 4 tools comprise a visualizer, despite the fact that many more frameworks include analysis processes that depend on custom annotations not present in the original data sets. A final remark on the reporting capabilities: less than 30% of the surveyed tools offer a way to easily visualize data sets. A final remark on the reporting capabilities: less than 30% of the surveyed tools offer a way to easily visualize data sets. A final remark on the reporting capabilities: less than 30% of the surveyed tools offer a way to easily visualize data sets.

| Metric / Analysis | [13] | [16] | [17] | [18] | [19] | [22] | [23] | [25] | [24] | [27] | [28] | [29] | [31] | [32] | [36] | [33] | [34] | [35] | [37] | [39] | [40] |
|-------------------|------|------|------|------|------|------|------|------|------|------|------|------|------|------|------|------|------|------|------|------|------|------|
| Accuracy          | yes  | yes  | yes  | yes  | yes  | yes  | yes  | yes  | yes  | yes  | yes  | yes  | yes  | yes  | yes  | yes  | yes  | yes  | no    | no    | yes  | yes  | yes  |
| Precision         | no   | no   | no   | no   | no   | no   | no   | no   | no   | no   | no   | no   | no   | yes  | yes  | yes  | no   | no   | no   | no   | no   | no   |
| Recall            | no   | no   | no   | yes  | no   | no   | no   | no   | no   | no   | no   | no   | no   | yes  | no   | no   | no   | yes  | no   | no   | yes  | no   |
| ROC Curve         | -    | -    | -    | -    | yes  | -    | -    | -    | -    | no   | yes  | -    | no   | yes  | -    | no   | no   | -    | -    | -    | no   | -    |
| ROC AUC           | -    | -    | -    | -    | -    | yes  | -    | -    | -    | no   | yes  | -    | no   | yes  | yes  | yes  | yes  | no   | no   | no   | no   | -    |
| PR curve          | no   | no   | no   | yes  | no   | no   | no   | no   | no   | yes  | no   | no   | no   | yes  | no   | yes  | yes  | no   | no   | no   | yes  | no   |
| PR AUC            | no   | no   | no   | no   | yes  | no   | no   | no   | no   | no   | no   | no   | no   | yes  | no   | yes  | no   | no   | no   | no   | no   | no   |
| F1 Score          | no   | no   | no   | no   | no   | no   | no   | no   | no   | no   | no   | no   | no   | yes  | yes  | no   | yes  | no   | no   | no   | yes  | no   |
| F1 Curve          | no   | no   | no   | no   | no   | no   | no   | no   | no   | no   | no   | no   | no   | yes  | yes  | no   | yes  | no   | no   | no   | yes  | no   |
| FT AUC            | no   | no   | no   | no   | no   | no   | no   | no   | no   | no   | no   | no   | no   | yes  | yes  | no   | yes  | no   | no   | no   | yes  | no   |
| # FP              | no   | no   | no   | no   | no   | no   | no   | no   | no   | no   | no   | no   | no   | yes  | yes  | no   | yes  | no   | no   | no   | yes  | no   |
| # FN              | no   | no   | no   | no   | no   | no   | no   | no   | no   | no   | no   | no   | no   | yes  | yes  | no   | yes  | no   | no   | no   | yes  | no   |
| FN Analysis       | no   | yes  | no   | yes  | no   | yes  | no   | yes  | no   | yes  | no   | yes  | no   | yes  | no   | yes  | no   | no   | yes  | no   | yes  | no   |
| FP Analysis       | yes  | yes  | no   | yes  | no   | yes  | no   | yes  | yes  | yes  | yes  | yes  | yes  | yes  | no   | yes  | no   | yes  | no   | yes  | yes  | no   |
| TP Analysis       | no   | no   | no   | no   | yes  | no   | no   | no   | no   | no   | no   | no   | no   | yes  | no   | yes  | no   | no   | yes  | no   | yes  | no   |
| Reliability       | no   | no   | no   | no   | no   | no   | no   | no   | no   | no   | no   | no   | no   | yes  | no   | yes  | no   | no   | no   | yes  | no   | yes  |

TABLE II
MULTI-TASK METRICS AND ANALYSES.

| Metric / Analysis | [26] | [25] | [30] | [31] | [35] |
|-------------------|------|------|------|------|------|
| Error Rate        | no   | no   | no   | no   | yes  |
| Confusion Matrix  | yes  | yes  | yes  | yes  | no   |
| Mean Error        | no   | no   | no   | yes  | no   |
| Mean Absolute Error| no  | no   | no   | yes  | no   |
| Odds Ratio        | no   | yes  | no   | no   | no   |
| Matthew Correlation Coefficient | no | no | no | yes | no |
| TN Analysis       | no   | no   | no   | no   | yes  |

TABLE III
CLASSIFICATION-SPECIFIC METRICS AND ANALYSES.

| Metric / Analysis | [14] | [15] | [17] | [18] | [19] | [21] | [23] | [24] | [27] | [28] | [32] | [36] | [33] | [34] | [39] | [40] |
|-------------------|------|------|------|------|------|------|------|------|------|------|------|------|------|------|------|------|
| Mean IoU          | no   | no   | no   | yes  | no   | yes  | yes  | yes  | no   | yes  | yes  | yes  | yes  | yes  | yes  | yes  | yes  |
| Average Precision (IoU)| no  | yes  | no   | yes  | yes  | yes  | yes  | yes  | yes  | yes  | yes  | yes  | yes  | yes  | yes  | yes  | yes  |
| Average Recall (IoU)| no  | yes  | no   | no   | no   | no   | no   | no   | no   | yes  | yes  | yes  | yes  | yes  | yes  | yes  | yes  |
| Miss Rate         | yes  | no   | no   | no   | no   | no   | yes  | -    | -    | no   | yes  | no   | no   | no   | no   | no   | no   |
| Localization Latency | no | no | yes | no | no | no | no | no | no | no | no | no | no | no | no | no |
| IoU Analysis      | no   | no   | no   | yes  | yes  | yes  | yes  | yes  | no   | yes  | no   | yes  | no   | yes  | no   | yes  | no   |

TABLE IV
LOCALIZATION-SPECIFIC METRICS AND ANALYSES.

V. ISSUES AND RESEARCH DIRECTIONS

Black-box error diagnosis is a viable complement to interpretability techniques for achieving a deeper understanding of the performances of DNNs. However, the panorama of the tools and frameworks that support error diagnosis shows that there are still margins for improvement and research before full maturity is attained.
A. Open issues

The analysis of the surveyed tools reveals several open issues.

- **Consensus**: there is little agreement among the tools addressing the same task about the core set of metrics and analyses that are most beneficial to performance and error diagnosis. Table [VIII] shows task by task the percentages of tools that implement each metric. A common effort to define a core set of metrics per task would need to go beyond the provision made by the standard performance benchmarks focused on end-to-end evaluation with only a few metrics. The definition of a consensus set of metrics and analyses would promote the design of methodological guidelines for black-box error diagnosis based on fundamental performance indicators and diagnosis reports.

- **Workflow coverage**: all the analyzed tools focus on inference diagnosis with few considering also data set creation and annotation. Thus, a complete training and evaluation workflow would require the use of several frameworks and tools, each with its own input/output for- mats, configuration, metrics, and visualizations/reports. Integrating the pre-processing and training step and the testing and diagnosis step would allow developers to better understand the impact of hyperparameter configurations on output errors and compare different training processes and models.

- **Visual analytics and support for qualitative analysis**: the surveyed tools include almost only quantitative metrics or analyses that are useful to measure model performance or diagnose errors. In particular, when dealing with visual data, these measures are not enough to fully understand the model behavior. Qualitative analysis is fundamental to visualize both errors and correct predictions.

### TABLE V

**Graph Classification, Object Tracking and Pose Estimation metrics and analyses.**

| Metric / Analysis                                      | [21] | [24] | [27] | [28] | [29] | [32] | [33] | [39] | [40] |
|--------------------------------------------------------|------|------|------|------|------|------|------|------|------|
| Node Degree (Graph)                                    | -    | -    | yes  | -    | -    | -    |      |      |      |
| Shortest path distance to train nodes (Graph)          | -    | -    | yes  | -    | -    | -    |      |      |      |
| Nearest train nodes path distribution (Graph)          | -    | -    | yes  | -    | -    | -    |      |      |      |
| Nearest train nodes dominant label consistency (Graph) | -    | -    | yes  | -    | -    | -    |      |      |      |
| Label distribution of top-k train nodes with the most similar features (Graph) | -    | -    | yes  | -    | -    | -    |      |      |      |
| Top-k most similar training nodes dominant label consistency (Graph) | -    | -    | yes  | -    | -    | -    |      |      |      |
| Center-neighbor consistency rate (Graph)               | -    | -    | yes  | -    | -    | -    |      |      |      |
| Success Score (OT)                                     | -    | -    | yes  | -    | -    | -    |      |      |      |
| Failure Rate (OT)                                      | -    | -    | yes  | -    | -    | -    |      |      |      |
| Consistency Analysis (OT)                              | -    | -    | yes  | -    | -    | -    |      |      |      |
| Spatio-temporal Tube Average Precision (STT-AP) (OT)   | -    | -    | yes  | -    | -    | -    |      |      |      |
| Pose Estimation Average Precision (PE)                 | yes  | no   | -    | -    | -    | -    |      |      |      |
| Average Viewpoint Precision(PE)                        | yes  | no   | -    | -    | -    | -    |      |      |      |
| Average Orientation Similarity(PE)                     | yes  | no   | -    | -    | -    | -    |      |      |      |
| Mean Angle Error (PE)                                  | yes  | no   | -    | -    | -    | -    |      |      |      |
| Median Angle Error (PE)                                | yes  | no   | -    | -    | -    | -    |      |      |      |
| Object Keypoint Similarity (PE)                        | no   | yes  | -    |      |      |      |      |      |      |

### TABLE VI

**Error categorization metrics and analysis.**

| Metric / Analysis                                      | [15] | [17] | [21] | [22] | [24] | [27] | [28] | [29] | [32] | [33] | [39] | [40] |
|--------------------------------------------------------|------|------|------|------|------|------|------|------|------|------|------|------|
| Errors Categorization (ET)                             | yes  | yes  | yes  | yes  | yes  | yes  | yes  | yes  | yes  | yes  | yes  | yes  |
| ET: Classification                                     | yes  | no   | no   | no   | no   | no   | no   | yes  | no   | no   | yes  | no   |
| ET: Localization                                       | yes  | yes  | no   | yes  | yes  | yes  | yes  | yes  | yes  | yes  | yes  | no   |
| ET: Classification + Localization                      | no   | no   | no   | no   | no   | no   | no   | yes  | no   | no   | yes  | no   |
| ET: Duplicated                                        | yes  | no   | no   | no   | no   | no   | no   | yes  | no   | no   | yes  | no   |
| ET: Missed Ground Truth                                | no   | yes  | no   | no   | no   | yes  | no   | yes  | no   | yes  | no   | yes  |
| ET: Confusion with background                          | yes  | yes  | -    | yes  | no   | yes  | yes  | yes  | yes  | yes  | yes  | yes  |
| ET: Confusion with similar class                       | yes  | yes  | -    | no   | no   | no   | no   | yes  | no   | no   | yes  | no   |
| ET: Confusion with non similar class                   | yes  | no   | -    | no   | no   | no   | no   | yes  | no   | no   | yes  | no   |
| ET: Other                                              | yes  | yes  | yes  | yes  | yes  | yes  | no   | no   | yes  | yes  | yes  | yes  |
| ET: Opposite (PE)                                      | -    | no   | yes  | -    | -    | -    | -    | -    | -    | -    | -    | -    |
| ET: Nearby (PE)                                        | -    | no   | yes  | -    | no   | -    | -    | -    | -    | -    | -    | -    |
| ET: Confusion with other class with same object        | -    | -    | -    | yes  | no   | -    | -    | -    | -    | -    | -    | -    |
| ET: Confusion with other class with same verb          | -    | -    | -    | yes  | no   | -    | -    | -    | -    | -    | -    | -    |
| ET: Boundary                                           | -    | -    | -    | yes  | no   | -    | -    | -    | -    | -    | -    | -    |
| Error Contribution Analysis                            | yes  | yes  | yes  | yes  | yes  | no   | yes  | yes  | yes  | no   | yes  | yes  |

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and, associated with interpretability techniques, may help discover unwanted correlations. The visualization interfaces offered by error diagnosis tools could be extended to support the automatic selection and visualization of data samples relevant for qualitative analysis, e.g., those falling into given ranges of one or more output metrics.

- **Automatic extraction of properties**: additional properties associated to the input data have been shown to be beneficial in diagnosing and categorizing errors. Such properties in part can be automatically derived from the data (e.g., image color space, bounding box size, difficulty and quality level, number of objects, etc.). In contrast, others require the intervention of the user (e.g., domain-dependent object characteristics). Some of the analyzed tools compute only elementary properties (e.g., bounding box size or image color scheme) and none integrate an approach to extract non trivial diagnosis-oriented properties automatically. Very few tools integrate a GUI supporting data annotation.

- **Data quality assessment**: errors that are attributed to the model may be due to the presence of noise in the ground truth annotations (e.g., the same model on different data sets from the same domain may produce different error types). Only few tools integrate the analysis of the data set quality and the diagnosis of errors and provide head to head comparison of the same model on different data sets. A particular case of data quality analysis is bias detection in the input data set, which is the subject of a completely distinct family of tools but is supported only by one black-box error diagnosis framework.

- **Scalability**: the authors of several tools openly admit that their framework cannot be applied to very large data sets, featuring many samples, many classes, or many custom properties. The difficulty stems from both the computational effort required (e.g., graph metrics are computationally heavy) and from the visualization of results (traditional plots, interactive views, and summaries get cluttered and difficult to read).

- **Architecture and API standardization**: Albeit most tools publish their implementation code in open source repositories, the lack of a common architecture and of standard APIs makes the implementation of metrics, property extractors and visualizations/reports non portable and requires the re-implemention or the wrapping of even the most basic performance indicators to use them inside a specific framework. The definition of a plug-in architecture and of standard module interfaces is typical in more mature fields such as software development, as witnessed e.g., by the popular Eclipse and JetBrains frameworks. A similar approach applied to black-box diagnosis tools and more generally to DNN workflow management tools would promote the development of a community-managed library of reusable metrics, property extractors and visualizations/reports which could be installed rather than re-implemented in any given framework.

### B. Research directions

The review of DNNs black-box diagnosis frameworks uncovers many research challenges that are still to be pursued.

- **Integration of black-box diagnosis and interpretability techniques**: interpretability in machine learning is defined as “the ability to explain or to present in understandable terms to a human” how a model makes a prediction. The interpretability of DNNs has attracted increasing attention by researchers due to the impact that this class of algorithms has in critical domains such as medicine, economy, safety and social sciences. Interpretability techniques offer a view of the system behavior alternative but closely related to that afforded by black-box error diagnosis. They seek to unveil interpretability factors i.e., human-understandable concepts and processes that are at the base of the model prediction. Black-box error diagnosis and performance break down can aid the discovery of interpretability factors: if a model consistently fails or succeeds when the input exhibits certain human-defined properties, this is a hint that such properties play a role in the interpretability. For example, if a system for iconography classification in art images consistently classifies representations of a given subject (e.g., images of Saint Jerome in Christian art paintings) with more accuracy and confidence when the input contains distinctive symbols (e.g., a lion couched at the saint’s feet or the cardinal’s galer) this finding could attest the interpretative value of such symbols in the classification of that character. The relationship between interpretability and black-box analysis is exploited in methods, such as, that aim at discovering interpretability factors by modifying the input data and then measuring the changes in the output (e.g., by suppressing some features or masking part of an image). In computer vision a DNN interpretability approach alternative to the black-box analysis “opens the box” of the model and studies internal aspects such as the gradient flowing through the network and the regions of the input or of the inner feature maps that have most impact on the output. These methods enable the computation of saliency or attention maps that highlight the pixels that are more important for the classification of the image. A tool that integrates black-box analysis based on human-provided properties and local interpretability factors based on automatically extracted saliency maps could help control both performance and interpretability in the model design. A step in this direction is the SECA system, which uses crowdsourced conceptual labels associated to saliency maps to enable explanation queries about the inference made by DNNs for image classification. The interpretability factors derived in this way could be exploited for error diagnosis and performance break down bridging the gap between performance-oriented and interpretation-oriented model evaluation.

- **Integration of error diagnosis and runtime performance analysis**: at the beginning of their diffusion DL
models were designed to obtain the best possible performance on GPU-accelerated systems. With the emergence of mobile and edge AI applications the portability of DL models to constrained hardware (e.g., mobile phones and embedded devices) has become a major research topic [52]. The profiling of models (e.g., with metrics based on throughput, occupied memory, latency, or operation level) helps optimize architectures and support math-limited or memory-limited devices. Some techniques have been proposed, such as model pruning and quantization, but their automatic application and the parameters optimization search are still ongoing research. Only one tool among the surveyed ones integrates runtime performance analysis and some elementary diagnosis functions such as accuracy checking and model comparison. Given that in hardware-constrained scenarios the trade off between accuracy and runtime performances is a prominent concern, integrating the two perspectives would produce a constraint-aware tool extending the applicability of error diagnosis and performance break down to scenarios with hardware limitations.

- **Model design guidance**: deep neural models are not mere data driven tools. They embody a lot of prior knowledge expressed implicitly in the structure of the architecture, in the selection of the operators and in the definition of the training strategy and of the data set. A recent research field, the so called automated deep learning (AutoDL), addresses the combined selection and hyperparameter optimization of classification algorithms problem [53], [54] for the case of DL models. AutoDL research investigates the design patterns that can be applied to support or even minimize the human effort in the definition of optimal DL models for a variety of tasks [55], [59]. Current methods mostly rely on neural architecture search, which applies a rather brute force architecture and hyperparameter space exploration approach to the distillation of the best model for a given task. An extremely interesting evolution of the future error diagnosis frameworks would be to turn them into tools capable not only of diagnosing problems, but also to recommend model improvements. This would require a mapping between the model weaknesses identified by error diagnosis and a portfolio of model refactoring and improvement operators distilling the current wisdom of manual and automated DL design. Such a progress would somehow reconcile the practices of software development and data driven model design, which are now regarded as completely secluded and move the AutoDL field beyond the mere neural architecture search.

- **New task and data types**: As shown in Table the surveyed frameworks focus mostly on classification and localization tasks. The black-box error diagnosis approach and tools could benefit also other domains especially those featuring complex data and non trivial performance indicators. A notable example is the application of deep learning inference methods to temporal data series for such applications as anomaly detection [57], [58] and predictive maintenance [59]. In this area little work has been done to implement tools that offer off-the-shelf black-box diagnosis of errors and performance breakdown functionalities [60]. The data sets in these domains are usually characterized by many domain-dependent properties (e.g., the sampling frequency or the type and characteristics of the physical signal under investigation and of the corresponding acquisition sensor) which enable the break down of performance indicators and the attribution of errors to specific features of the input. Several research and commercial frameworks support the workflow of anomaly detection and predictive maintenance applications but do not support error attribution and metrics break down. An example is the RELOAD tool [61] which aids the ingestion of data, the selection of the most informative features, the execution of multiple anomaly detection algorithms, the evaluation of alternative anomaly identification strategies, the evaluation of multiple metrics and the visualization of results in a GUI. RELOAD implements multiple metrics and algorithms off-the-shelf and has an extensible architecture. However it does not support yet the break down of performance metrics and the attribution of errors based on the features of the input.

**VI. Conclusions**

In this survey, tools for the black-box diagnosis of errors in deep learning models were presented. Major properties that would guide the user choice have been discussed and analyzed: supported tasks and media types, implemented metrics and analyses, additional functionalities, customization capabilities and openness. Novelties, advantages and disadvantages of the surveyed works have been described to provide the reader with a clear and up to date view of the field. Metrics, analyses and functionalities have been collected from each work and grouped by task to ease the comparison between the tools with a common focus. Several issues emerged from the survey have been discussed and the most promising research directions have been highlighted to help improve the present status of the art.

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VII. BIOGRAPHY

Pierro Fraternali is full professor of Web Technologies at Politecnico di Milano. Author of more than 200 papers in international peer reviewed conferences and journals (H index 43) and of four international books. His main research interests concern methodologies and tools for WEB/mobile application development, socio-technical system design, gamification and serious games. He is author of several articles on International Journals and Conference Proceedings, and a number of books. He is co-author of OMG’s IFML standard and co-founder of WebRatio a start-up focused on the commercialization of a tool suite for the Model-Driven Development of Web/mobile cloud-powered applications.

Federico Milani is a PHD student and research assistant in the Web data and society group at Politecnico di Milano. He is working in the development of novel methodologies for visual data analysis applicable to environmental and conservation applications and for the design of integrated development environments for developing and debugging Deep Learning algorithms and models.

Rocio Nahime Torres received the M.Sc. degree in Computer Science from the “Universidad Nacional de La Plata” (National University of La Plata), Argentina. She is a PHD student and research assistant in the Web data and society group at Politecnico di Milano. She is working in the development of mobile applications for crowdsourcing and environmental data collection and on Deep Learning methods for the analysis of data for environmental applications.

Niccolò Zangrando Niccolò Zangrando received the M.Sc. degree in Computer Science and Engineering at Politecnico di Milano, Italy, in 2021. He is a research assistant in the Web data and society group. He is working in the development of inference and diagnosis techniques for the analysis of complex data including IoT streams, temporal data series and images.
### Table VII
**Additional features**

| Feature                      | 14 | 15 | 16 | 17 | 18 | 19 | 20 | 21 | 22 | 23 | 24 | 25 | 26 | 27 | 28 | 29 | 30 | 31 | 32 | 33 | 34 | 35 | 36 | 37 | 38 | 39 | 40 |
|------------------------------|----|----|----|----|----|----|----|----|----|----|----|----|----|----|----|----|----|----|----|----|----|----|----|----|----|----|----|----|
| Overall Analysis             | yes| yes| no | yes| yes| yes| yes| yes| yes| yes| yes| yes| no | yes| yes| no | yes| yes| yes| yes| yes| yes| yes| yes| yes| yes| no | yes| yes| yes| yes|
| Per class Analysis           | no | yes| no | yes| yes| yes| no | yes| no | yes| no | yes| no | yes| no | yes| no | yes| no | yes| yes| yes| yes| yes| yes| yes| no | yes| yes| no | no |
| Per property Analysis        | yes| yes| yes| no | yes| no | no | yes| yes| yes| yes| yes| no | yes| yes| yes| yes| yes| no | yes| no | yes| no | yes| yes| no | yes| yes| no | yes| yes|
| Overall report               | no | no | no | yes| no | no | no | yes| no | yes| no | yes| no | yes| yes| no | yes| no | yes| no | yes| no | yes| yes| no | yes| yes| no | yes| yes| yes|
| Per property report          | yes| no | no | yes| no | no | no | yes| no | no | no | no | no | no | no | no | yes| no | no | yes| no | no | yes| no | yes| no | no | yes| no | no | no |
| Builtin input properties     | yes| yes| yes| no | yes| no | yes| yes| yes| yes| yes| yes| no | yes| no | yes| no | yes| no | yes| yes| no | yes| no | yes| yes| no | yes| yes| no | no |
| User-defined properties      | no | no | no | no | yes| no | no | no | yes| no | no | no | yes| no | yes| yes| yes| yes| yes| no | yes| no | yes| yes| no | yes| no | yes| no | no | no |
| Models comparison            | yes| no | yes| no | yes| no | no | yes| yes| yes| yes| yes| no | yes| yes| yes| yes| yes| no | yes| yes| yes| yes| yes| yes| no | yes| yes| no | no |
| User-defined metrics         | no | no | no | no | no | no | no | no | no | no | no | no | no | no | no | no | no | no | no | no | no | no | no | no | no | no | no | no | no | no | no |
| Property distribution        | no | no | no | no | no | no | no | no | no | no | no | no | yes| no | yes| no | yes| no | no | no | yes| no | no | yes| yes| yes| yes| yes| yes| yes| yes|
| Class distribution           | no | no | no | no | no | no | no | no | no | no | no | no | no | no | no | no | no | no | no | no | no | no | no | no | no | no | no | no | no | no | no |
| Annotator                    | no | no | no | no | no | no | no | no | no | no | no | no | no | no | no | no | no | no | yes| no | yes| no | yes| no | yes| no | no | yes| no | no | no |
| Visualizer                   | no | no | no | no | no | no | no | no | no | no | no | no | no | no | no | no | no | no | yes| yes| yes| yes| yes| yes| yes| yes| no | yes| no | no | no |

**Notes:**
- **Yes**: Feature is available.
- **No**: Feature is not available.
- **?**: Feature is optional.

**Columns:**
- **14-40**: Feature numbers corresponding to the features listed in the table.
### TABLE VIII

The tools that implement each metrics in percentage. Each column represents a task or a family of related tasks and shows the number of tools that support it.

| Metrics-Analysis/Task                  | CL (10) | OD/IS/SS (14) | PE (3) | AD (2) | OT (2) | VRD (1) |
|----------------------------------------|---------|---------------|--------|--------|--------|---------|
| **Accuracy**                           | 70% (7) |               | 14% (2) | 0% (0) | -      | -       |
| **Error Rate**                         | 10% (1) | -             | -      | -      | -      | -       |
| **Precision**                          | 10% (1) | -             | -      | -      | -      | -       |
| **Recall**                             | 10% (1) | -             | -      | -      | -      | -       |
| **F1 score**                           | 10% (1) | -             | -      | -      | -      | -       |
| **Average Precision**                  | 10% (1) | 29% (4)       | 53% (1) | 0% (0) | 50% (1) | 0% (0) |
| **Average Recall**                     | 10% (1) |               | 29% (4) | 53% (1) | 0% (0) | 50% (1) | 0% (0) |
| **ROC AUC**                            | 40% (4) | -             | -      | -      | -      | -       |
| **Precision-Recall AUC**               | 40% (4) | 7% (1)        | 0% (0) | 0% (0) | 0% (0) | 0% (0) |
| **F1 AUC**                             | 10% (1) | 7% (1)        | 0% (0) | 0% (0) | 0% (0) | 0% (0) |
| **Mean Error**                         | 10% (1) | -             | -      | -      | -      | -       |
| **Mean Absolute Error**                | 10% (1) | -             | -      | -      | -      | -       |
| **Mean Squared Error**                 | 10% (1) | -             | -      | -      | -      | -       |
| **Odds Ratio**                         | 10% (1) | -             | -      | -      | -      | -       |
| **Matthews Correlation Coefficient**   | 20% (2) | -             | -      | -      | -      | -       |
| **Mean Intersection Over Union (Mean IoU)** | -        | 21% (3)       | 0% (0) | 0% (0) | 100% (2) | 0% (0) |
| **Miss Rate**                          | 10% (1) | -             | -      | -      | -      | -       |
| **Localization Latency**               | 10% (1) | -             | -      | -      | -      | -       |
| **Node Degree**                        | 10% (1) | -             | -      | -      | -      | -       |
| **Shortest path distance to train nodes** | 10% (1) | -             | -      | -      | -      | -       |
| **Nearest train nodes dominant label consistency** | 10% (1) | -             | -      | -      | -      | -       |
| **Top-k most similar training nodes dominant label consistency** | 10% (1) | -             | -      | -      | -      | -       |
| **Center-neighbor consistency rate**   | 10% (1) | -             | -      | -      | -      | -       |
| **Success Score**                      | -       | -             | -      | -      | 50% (1) | -       |
| **Failure Rate**                       | -       | -             | -      | -      | 50% (1) | -       |
| **Spatio-Temporal Tube Average Precision (STT-AP)** | - | - | - | 50% (1) | - | - |
| **Average Viewpoint Precision**        | -       | -             | -      | -      | 50% (1) | -       |
| **Average Orientation Similarity**     | -       | -             | -      | -      | -      | -       |
| **Mean Angle Error**                   | -       | -             | -      | -      | -      | -       |
| **Median Angle Error**                 | -       | -             | -      | -      | -      | -       |
| **Object Keypoint Similarity**         | -       | -             | -      | -      | -      | -       |
| **Curves**                             | 30% (3) | -             | -      | -      | -      | -       |
| **ROC curve**                          | 30% (3) | -             | -      | -      | -      | -       |
| **Precision-Recall curve**             | 30% (3) | 14% (2)       | 33% (1) | 0% (0) | 0% (0) | 0% (0) |
| **F1 curve**                           | 10% (1) | 7% (1)       | 0% (0) | 0% (0) | 0% (0) | 0% (0) |
| **Confusion Matrix**                   | 70% (7) | -             | -      | -      | -      | -       |
| **# True Positives (TP)**              | 10% (1) | -             | -      | -      | -      | -       |
| **# False Positives (FP)**             | 20% (2) | 14% (2)       | 0% (0) | 0% (0) | 0% (0) | 0% (0) |
| **True Positive Analysis**             | 10% (1) | 7% (1)       | 0% (0) | 0% (0) | 0% (0) | 0% (0) |
| **False Positive Analysis**            | 10% (1) | 50% (5)       | 66% (2) | 50% (1) | 0% (0) | 100% (1) |
| **False Negative Analysis**            | 10% (1) | 29% (4)       | 66% (2) | 50% (1) | 0% (0) | 100% (1) |
| **Error Contribution Analysis**        | 10% (1) | -             | -      | -      | 50% (1) | 0% (0) |
| **Intersection Over Union Analysis**   | -       | 36% (5)       | 33% (1) | 0% (0) | 50% (1) | 0% (0) |
| **Reliability Analysis**               | 10% (1) | 7% (1)       | 0% (0) | 0% (0) | 50% (1) | 0% (0) |
| **Temporal Reasoning**                 | -       | -             | -      | 50% (1) | 0% (0) | -       |
| **Person-based Reasoning**             | -       | -             | -      | 50% (1) | 0% (0) | -       |
| **Qualitative Analysis (Visualizer)**  | 20% (2) | 21% (3)       | 0% (0) | -      | 0% (0) | 0% (0) |
| **Nearest train nodes path distribution** | 10% (1) | -             | -      | -      | -      | -       |
| **Label distribution of top-k train nodes with the most similar features** | 10% (1) | -             | -      | -      | -      | -       |