

BDD-based Analysis of Classifier Availability under Feature Uncertainty

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Abstract—Machine learning classifiers operating in real-world environments may be affected by observation errors in input features. This paper proposes a Binary Decision Diagram (BDD)-based method for analysing classifier availability under feature uncertainty. The approach interprets a classifier as a structure function and applies concepts from reliability analysis to investigate the robustness of classification decisions. Feature uncertainty is represented by observation error probabilities assigned to input attributes, while classifier availability is defined as the probability of preserving the classification result under distorted input conditions. A BDD representation enables efficient and exact availability computation. The proposed method is evaluated using the SPECT Heart dataset. The results demonstrate the applicability of reliability analysis methods to machine learning models and provide additional insight into classifier robustness under uncertain input conditions.

Keywords—Classifier Availability, Binary Decision Diagram, Structural Importance, Reliability Analysis, Feature Uncertainty.

I. INTRODUCTION

Machine learning classifiers are increasingly used in applications where decision quality and robustness are important requirements. In practical environments, however, input data are often affected by measurement errors, sensor inaccuracies, or preprocessing imperfections [1-3]. Such distortions may alter the values of input features and consequently change classification outcomes. Therefore, in addition to predictive accuracy, it is important to evaluate a classifier's ability to maintain its decisions under uncertain input conditions [1, 4].

A number of approaches have been proposed to analyse feature influence and classifier interpretability [1, 4-6]. Most of them focus on feature importance, explainability, or predictive performance. However, considerably less attention has been devoted to analysing classifier behaviour from a reliability perspective, particularly with respect to the impact of feature observation errors on decision robustness. As a result, the

availability of classification decisions under feature uncertainty remains insufficiently investigated.

Although numerous studies investigate feature importance, explainability, and predictive performance, considerably less attention has been devoted to the robustness of classification decisions under feature observation errors [1-3, 5, 6]. Existing approaches typically focus on identifying influential attributes or explaining classifier outputs, but they do not provide a probabilistic assessment of whether a classification decision will be preserved when input features are observed incorrectly. Consequently, the reliability-oriented notion of classifier availability remains largely unexplored.

Reliability analysis offers a mature mathematical framework for quantifying the effect of component failures on system behaviour [3, 4, 7, 8]. If input features are interpreted as system components and feature observation errors as component failures, reliability concepts can be naturally transferred to machine-learning models. This interpretation creates an opportunity to analyse classifier robustness using formally defined probabilistic measures rather than empirical perturbation experiments alone.

This paper introduces a reliability-oriented framework for analysing machine-learning classifiers under feature uncertainty. The proposed approach defines classifier availability as the probability of preserving a classification decision despite observation errors in input features. To enable efficient exact evaluation, the classifier is represented as a Binary Decision Diagram (BDD) [9], which allows uncertainty propagation and probabilistic analysis within a unified structure. In contrast to conventional performance measures, the proposed availability metric quantifies decision robustness and provides complementary information to classification accuracy.

The proposed framework is evaluated using the SPECT Heart dataset [10]. The results demonstrate the applicability of reliability analysis methods to robustness assessment of classifiers and provide additional insight into how machine learning models operate under uncertain input conditions.

The main contributions of this paper are as follows: (i) introduction of classifier availability as a reliability-oriented measure of decision robustness under feature uncertainty; (ii) formal probabilistic model relating feature observation errors to classification decision preservation; (iii) exact availability

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evaluation using BDDs instead of exhaustive enumeration of uncertainty scenarios; (iv) analysis of the relationship between Structural Importance and decision robustness within a reliability framework.

While existing studies predominantly focus on feature importance, explainability, or predictive performance, this work addresses a complementary problem: quantifying the probability that a classifier preserves its decision under uncertain input conditions.

II. BACKGROUND

The reliability analysis requests the representation of the investigated object by a mathematical model. There are different mathematical models in reliability analysis [11]. One large group of mathematical models is characterised by considering two states in the behaviour of the investigated object and its components. These mathematical models, called the Binary State System (BSS), assume only functioning and failure states for reliability analysis. BSS can be represented in different ways, and one is the structure function [4, 9].

A. Structure function

Let a BSS consist of n components. Its behaviour and, as a result, its reliability depend on the components' states. This dependence is defined by the structure function, in which the function values represent system reliability and its components' states are values of variables x_i ($i = 1, 2, \dots, n$):

$$\phi(x_1, \dots, x_n) = \phi(\mathbf{x}): \{0,1\}^n \rightarrow \{0,1\}, \quad (1)$$

In (1), the component breakdown and system failure are indicated by values 0 of the variables and the function. Consequently, the operational states of the system and its components are represented by the value 1. The reliability analysis supposes the indication of component probability states that are introduced as $p_i = \Pr\{x_i = 1\}$ and $q_i = \Pr\{x_i = 0\}$.

The structure function (1) in reliability analysis can be represented as a fault tree, a reliability block diagram, a Hasse diagram, or a BDD [9]. BDD is often used last because it enables effective processing of large-dimensional systems.

BDD is a graphical model. It consists of two terminal nodes labelled 0 and 1, corresponding to the possible output values of the structure function. The internal nodes represent variables x_i ($i = 1, \dots, n$), which correspond to individual system components. Each internal node is connected to two outgoing edges describing the alternative states of the associated component. In reliability applications, the outgoing edges may also be assigned probabilities representing component-state occurrences as p_i and q_i . It allows us to compute metrics, indices and measures for reliability evaluation.

B. Structural Importance

Reliability evaluates the system as a whole and does not allow tracing the impact of each component on the system's behaviour. This problem is addressed by the Importance Analysis of reliability. It determines, by special measures, how the system's state will change if the state of one or more of its components changes. Among these measures, the *Structural Importance* (SI) measure occupies a special place. Based on the

structural interrelations of the system or its topological properties, defined by the structural function, it indicates the probability of changes in the system's state if the state of one of its components changes [12]:

$$SI_i = \rho_i / 2^{n-1} \quad (2)$$

where ρ_i is the number of the system's critical states of the i -th component for which a change in its state also causes a change in the system's performance.

The number ρ_i in (2) can be defined as non-zero values of the *Direct Partial Boolean Derivatives* (DPBD) of the structure function with respect to variable x_i [12]:

$$\frac{\partial \phi(j \rightarrow h)}{\partial x_i(j \rightarrow h)} = \begin{cases} 1, & \text{if } \phi(j_i, \mathbf{x}) = j \text{ and } \phi(h_i, \mathbf{x}) = h \\ 0, & \text{in the other case} \end{cases}, \quad (3)$$

where $j, h = \{0,1\}$ and $j = 1$ and $h = 0$ for the system failure.

C. Relationship Between Reliability Systems and Classifiers

Above, the reliability analysis was introduced for a system analysis, but other objects can be treated as systems for reliability analysis. For example, in study [4], the correlation between the reliability analysis system and the classifier has been considered. The short result of this correlation for feature analysis can be presented in Table I.

TABLE I. CORRELATION OF THE TERMINOLOGIES OF FEATURE IN MACHINE LEARNING AND SYSTEM IN RELIABILITY ANALYSIS

Reliability Analysis	Feature Analysis
Component	Feature
Component state	Feature value
Structure function	Classifier
System state	Classification result (output feature)
Component failure	Feature observation error

The correspondence presented in Table I enables the direct application of reliability analysis concepts and methods to classification models. In this interpretation, a classifier can be viewed as a system whose behaviour is determined by the states of its components, represented by input features. Consequently, mathematical tools developed for system reliability analysis can be employed to investigate the behaviour of machine learning classifiers.

Most existing studies have focused on evaluating feature importance [1-3], in which input attributes are analysed for their influence on classification outcomes. However, from a reliability perspective, it is equally important to investigate how feature observation errors affect classifier operation. If input features are interpreted as system components, errors in feature values may be viewed as component failures, while a change in the classification result may be interpreted as a system malfunction. This analogy provides a basis for analysing classifier robustness using reliability-oriented methods.

The proposed approach extends the reliability interpretation of classifiers beyond feature importance analysis. It introduces a framework for modelling feature uncertainty and evaluating the availability of classification decisions under imperfect input conditions. The corresponding concepts and measures are presented in the following section.

III. RELIABILITY-BASED CLASSIFIER INTERPRETATION

A. Feature Uncertainty Model

The classification process usually assumes that all input attribute values are observed correctly. However, in real-world applications, attribute values may be affected by measurement errors, sensor inaccuracies, missing values, data transmission errors, or preprocessing errors. As a result, the values available to the classifier may differ from the actual values describing the observed object.

To evaluate a classifier's robustness under imperfect input conditions, uncertainty is introduced into the attribute space. Let $\mathcal{A} = \{\mathcal{A}_1, \mathcal{A}_2, \dots, \mathcal{A}_n\}$ denote the set of binary input attributes. A specific input vector is denoted by $\mathbf{a} = (a_1, \dots, a_n) \in \{0, 1\}^n$, and its observed (possibly distorted) version by $\mathbf{a}^* = (a_1^*, \dots, a_n^*)$. For each attribute i , the observation error probability is defined as

$$q_i = \Pr(a_i^* \neq a_i). \quad (4)$$

The probability that the attribute value is observed correctly is

$$p_i = 1 - q_i. \quad (5)$$

For binary attributes, an observation error corresponds to a state inversion: $0 \rightarrow 1$ or $1 \rightarrow 0$. Consequently, the behaviour of each attribute can be modelled as a two-state component of a BSS.

Since the actual probabilities of observation errors are generally unknown, feature uncertainty is modelled using predefined error scenarios. For simplicity, all features are initially assigned the same error probability $q_i = q$. Several values of q are subsequently considered to analyse how increasing uncertainty affects the classifier behaviour.

The proposed uncertainty model does not modify the classifier itself. Instead, it affects the values presented to the classifier at its input. Therefore, any change in the classification result is solely due to distorted attribute values and their propagation through the decision structure. This interpretation establishes a direct correspondence between attribute errors in machine learning and component failures in reliability analysis, enabling the application of BDD-based reliability techniques to the evaluation of classifier robustness.

B. Classifier Availability

In practical applications, the values of input attributes may contain errors caused by sensor inaccuracies, data transmission failures, imperfect measurements, or preprocessing procedures. Such distortions can alter the decision path a classifier follows and, consequently, change the classification result. Therefore, in addition to predictive accuracy, it is important to evaluate a classifier's robustness to uncertainty in input attributes.

To evaluate the robustness of the classifier, we consider two random vectors: $\mathbf{A} = (A_1, \dots, A_n)$ is a random vector of true feature values, distributed according to the empirical distribution of the test dataset, and $\mathbf{A}^* = (A_1^*, \dots, A_n^*)$ is a random vector of observed feature values, where each A_i^* is obtained from A_i by independent bit flipping with probability q_i . For a

given realisation $\mathbf{a}$, the classifier output is $C = \phi(\mathbf{a})$. For its distorted version $\mathbf{a}^*$, the output is $C^* = \phi(\mathbf{a}^*)$.

The classifier is considered operational if the classification result remains unchanged despite the presence of attribute errors. Define the indicator function:

$$\psi(\mathbf{a}, \mathbf{a}^*) = \mathbb{I}[\phi(\mathbf{a}) = \phi(\mathbf{a}^*)], \quad (6)$$

which equals 1 if the classifications coincide and 0 otherwise.

The classifier availability is then defined as the expectation of this indicator over the joint distribution of $\mathbf{A}$ and the observation errors:

$$A_v = \mathbb{E}[\psi(\mathbf{A}, \mathbf{A}^*)] = \Pr(\phi(\mathbf{A}) = \phi(\mathbf{A}^*)). \quad (7)$$

This probability is computed efficiently using the BDD representation, with branches weighted by p_i and q_i .

The complementary probability

$$U_v = 1 - A_v \quad (8)$$

represents the classifier's unavailability and corresponds to the probability that errors in the input attributes lead to a change in the classification decision.

The proposed availability measure quantifies the robustness of classification outcomes rather than predictive performance. Unlike conventional classification metrics, such as accuracy or F-score, availability measures a classifier's ability to maintain its decision under uncertain input conditions. This interpretation is consistent with reliability analysis, in which system availability is the probability of maintaining the required functionality despite component failures.

Although accuracy is the most commonly reported performance metric in machine learning, it does not quantify the stability of classification decisions under uncertainty in the input. Accuracy measures predictive correctness with respect to ground-truth labels, whereas availability measures the preservation of decisions under feature observation errors. These characteristics address different aspects of classifier behaviour and are not necessarily correlated. A classifier with excellent predictive performance may still be vulnerable to small input distortions, while a more robust classifier may preserve its decisions with a higher probability. For this reason, classifier availability provides complementary information that cannot be directly inferred from conventional classification metrics.

Consequently, the proposed framework provides a reliability-oriented assessment of classifier robustness and identifies attributes with the greatest influence on classifier availability.

C. Structural Importance of Features

SI defined in (2) is a purely topological measure. It quantifies the proportion of all possible input configurations, 2^{n-1} , for which a change in the value of feature $\mathcal{A}_i$ (while keeping all other features fixed) results in a change in the classifier's output. This measure does not incorporate the joint probability distribution of the features. Therefore, it should be

interpreted as a structural indicator of a feature's influence on the classifier's decision logic, not as a probabilistic estimate of the real-world likelihood of an output change. Such a probabilistic interpretation is valid only under the assumption of independent, uniformly distributed features, which is a common simplification in structural reliability analysis but may not hold in real-world datasets.

D. BDD-Based Availability Analysis Procedure

The proposed framework combines classifier modelling, feature uncertainty analysis, and reliability assessment within a unified BDD-based representation. The general workflow of the proposed approach is illustrated in Fig. 1.

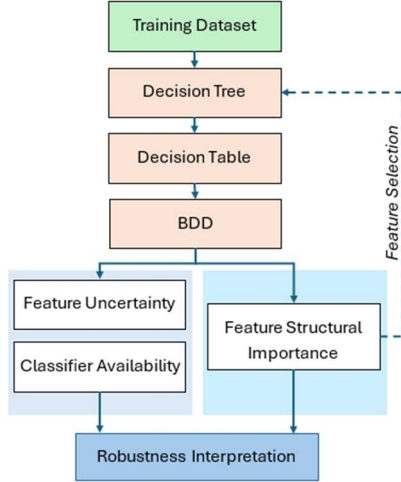


Fig. 1. Proposed framework for BDD-based classifier availability analysis.

The procedure starts by inducing a classifier from the training dataset. In this study, a Decision Tree classifier is used because its decision logic can be directly translated into BDD [9]. The BDD provides a compact and canonical representation of the classifier and enables efficient processing of all possible combinations of feature states. Furthermore, the probabilistic interpretation of BDD edges enables incorporating feature uncertainty into the analysis.

The resulting BDD can be used to analyse the classifier's availability. However, the importance of input attributes and their selection can also be assessed. Some low-importance input attributes can be removed during the feature selection procedure to induce a new classifier [4].

The uncertainty model introduced in Section III-A is then assigned to the BDD variables. For each feature A_i , the probabilities of correct observation p_i and observation error q_i are associated with the corresponding BDD branches. The resulting probabilistic BDD represents all possible distorted and non-distorted feature vectors together with their occurrence probabilities.

Based on this representation, the classifier's availability is evaluated according to (7). The analysis determines the probability that the classification result remains unchanged when feature observations are subject to errors. At the same time, the probability of decision modification can be obtained as the classifier's unavailability, as defined in (8).

To identify the most influential features, SI values are computed for all classifier attributes. The obtained importance ranking is subsequently compared with the degradation in availability caused by individual feature errors. This comparison enables investigation of the relationship between a feature's structural role and its impact on classifier robustness.

The proposed procedure integrates classical reliability analysis concepts with machine learning models and provides a quantitative assessment of classifier robustness under feature uncertainty.

IV. CASE STUDY

A. Dataset

The experimental evaluation was conducted using the SPECT Heart dataset obtained from the UCI Machine Learning Repository. The dataset contains 267 patient records described by 22 binary diagnostic features derived from Single Proton Emission Computed Tomography (SPECT) images [10]. Each record is assigned to one of two diagnostic classes: normal or abnormal cardiac conditions.

The binary nature of the dataset makes it particularly suitable for the proposed reliability-based analysis. Since all input features are binary, the induced classifier can be directly represented by a BDD without additional discretisation or transformation procedures.

Before analysis, the dataset was randomly split into training and test sets at a 70:30 ratio. The training subset was used for classifier induction, whereas the testing subset was used to evaluate classification performance and classifier availability under feature uncertainty.

B. Classifier Construction

A Decision Tree classifier was induced from the training data. The selection of Decision Trees was motivated by their transparent logical structure and the possibility of transforming them into a BDD.

The induced Decision Tree includes 22 attributes, 33 nodes, 34 leaves, and has a depth of 22 levels. The accuracy of this classifier is 0.95. Transforming this Decision Tree into BDD enables us to compute the importance of input attributes. The results (Table II) show that 7 attributes have an SI significantly higher than those of the other attributes. This information allows us to reduce the number of attributes using a feature selection procedure and to induce a new Decision Tree based on 7 attributes only (Fig. 2): $A_1, A_{11}, A_{13}, A_{16}, A_{17}, A_{21}, A_{22}$. The comparison of the initial Decision Tree and a new Decision Tree is shown in Table III.

TABLE II. STRUCTURAL IMPORTANCE OF INPUT ATTRIBUTES FOR THE DATASET SPECT

SI_1	SI_2	SI_3	SI_4	SI_5	SI_6	SI_7	SI_8	SI_9	SI_{10}	SI_{11}
0.5027	0.0001	0.0410	0.0103	0.0022	0.0001	0.0001	0.0101	0.0001	0.0021	0.7085
SI_{12}	SI_{13}	SI_{14}	SI_{15}	SI_{16}	SI_{17}	SI_{18}	SI_{19}	SI_{20}	SI_{21}	SI_{22}
0.0171	0.8327	0.0001	0.0001	0.6124	0.5027	0.0001	0.0001	0.0171	0.7029	0.5027

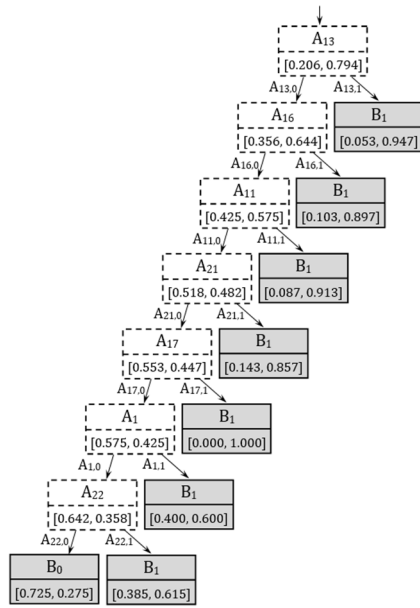


Fig. 2. Decision Tree for classifier availability analysis.

TABLE III. COMPARISON OF DECISION TREES FOR THE DATASET SPECT

Decision Tree	Features	Depth	Nodes Number	Accuracy
Original	22	22	33	0.950
Reduced	7	7	7	0.947

C. Feature Uncertainty Scenarios

Since real observation error probabilities were unavailable, a scenario-based analysis was employed. Four uncertainty levels were considered: $q \in \{0.01, 0.05, 0.10, 0.20\}$. For each scenario, all features were assigned the same observation error probability: $q_i = q, i = 1, \dots, n$. The corresponding probabilities of correct observation were determined as $p_i = 1 - q$. These scenarios represent progressively increasing levels of feature uncertainty and allow investigation of the relationship between input data quality and classifier availability.

D. Availability Evaluation Using BDD

To analyse the effect of feature uncertainty on classifier operation, the decision-preservation function defined in (6) was considered. The function ψ indicates whether the classification decision remains unchanged after feature observation errors occur.

A BDD representation of ψ (6) was constructed and the probabilities p_i (4) and q_i (5) were assigned to its branches according to the uncertainty model. Classifier availability was then obtained as the probability of reaching the terminal node corresponding to the state $\psi = 1$ according to (7). Similarly, classifier unavailability was computed as U_v in (8).

E. Structural Importance Analysis

In addition to the availability evaluation, Structural Importance values were calculated for all features of the induced classifier. According to the correspondence introduced in Table I, the input features were treated as system components and the classifier was interpreted as a structure function. SIs (2) of input attributes are computed using the DPBD (3). The obtained SI

values were used to rank the features according to their structural influence on classifier behaviour.

V. RESULTS AND DISCUSSION

A. Induced Decision Tree and BDD

The induced Decision Tree (Fig. 2) enables the construction of a BDD (Fig. 3) using the typical procedures for BDD construction [9]. This BDD is used for classifier analysis.

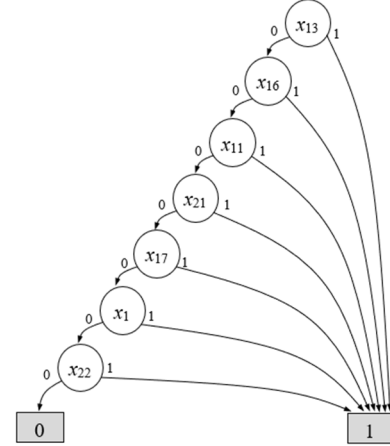


Fig. 3. BDD for classifier availability analysis.

B. Classifier Availability under Feature Uncertainty

The availability values obtained for the considered uncertainty scenarios are presented in Fig. 4. The results demonstrate the expected relationship between feature uncertainty and classifier availability. As the observation error probability q increases, the probability of preserving the classification decision gradually decreases. This behaviour confirms that feature observation errors affect the classifier's decision paths and may consequently alter the classification outcome.

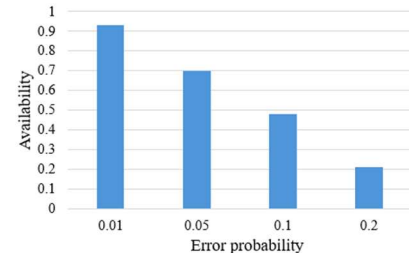


Fig. 4. Availability of the classifier (Fig.2) scenarios.

For low uncertainty levels ($q = 0.01$ and $q = 0.05$), the classifier maintains a high availability, indicating that occasional feature observation errors have only a limited influence on the final decision. However, further increases in uncertainty lead to a noticeable reduction in availability, suggesting that the cumulative effect of multiple feature errors may significantly alter the classifier's output.

The obtained results demonstrate that availability analysis provides information that cannot be derived from conventional classification metrics. While accuracy measures a classifier's predictive quality on a test dataset, availability quantifies the probability that the classifier maintains its decision under

uncertain input conditions. Consequently, availability can be interpreted as a reliability-oriented measure of classifier robustness.

From a practical perspective, the obtained results indicate that classifier robustness cannot be fully characterised by predictive accuracy alone. The considered classifier achieves high classification accuracy, yet its availability decreases as feature uncertainty grows. This observation confirms that predictive performance and decision robustness represent different characteristics of classifier behaviour. Therefore, evaluating availability may provide additional information when classifiers are deployed in environments where feature values are obtained from imperfect measurements or unreliable data sources. The BDD representation enabled exact computation of availability values without exhaustive enumeration of all possible combinations of feature errors. This confirms the suitability of BDDs for efficient reliability-oriented analysis of classification models represented by logical decision structures.

C. Structural Importance of Features

The calculated SI values for the reduced classifier are uniform ($SI_i = 0.0156$), which indicates a structurally balanced decision logic for this particular dataset. However, the main contribution of the SI calculation here is to validate our availability results: we confirmed that artificially inducing errors in any single feature leads to a nearly identical drop in Availability ($\Delta A_v \approx 0.002$), which is consistent with the uniform SI scores. This cross-validation demonstrates the coherence between the BDD-based structural analysis and the probabilistic availability assessment. This result also illustrates the potential relationship between structural and probabilistic robustness analysis.

Overall, the obtained results demonstrate that the proposed availability measure captures an aspect of classifier behaviour that is not directly reflected by conventional performance metrics. By quantifying the probability of decision preservation under feature uncertainty, availability analysis provides a complementary perspective on classifier robustness and supports reliability-oriented assessment of machine-learning models operating in imperfect environments.

VI. CONCLUSION

This paper proposed a BDD-based framework for analysing classifier availability under feature uncertainty. The approach combines a feature-uncertainty model, classifier-availability evaluation, and Structural Importance analysis within a unified reliability-oriented framework. The experimental study conducted on the SPECT Heart dataset demonstrated that BDDs enable efficient availability computation under feature observation errors. The obtained results confirm that reliability analysis concepts can be successfully applied to investigate the robustness of machine learning classifiers and provide additional insight into the structural role of input features. Future

work will focus on extending the proposed approach to other classifier architectures and investigating availability-preserving feature-selection strategies.

A limitation of the current study is that the proposed framework, in its present form, assumes feature independence when interpreting SI in probabilistic terms. In practice, features may be statistically dependent, which could lead to discrepancies between the structural importance ranking and the actual impact of errors in feature observations on classifier robustness. However, A_v defined in (7) remains valid, as it directly computes the probability of preserving the decision based on the assumed error probabilities q_i . Extending the framework to incorporate feature dependencies through joint probability distributions is a direction for future work.

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