Semantic Image Recognition using Ontologies

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Abstract

Machine learning is a widely employed statistical learning approach known for its remarkable performance across various fields. Nevertheless, it is not without its limitations, primarily stemming from its statistical nature. Some of these drawbacks include sub-optimal performance when confronted with limited data and scalability issues. To address these limitations and make machine learning solutions more versatile for a broader spectrum of projects and disciplines, we leverage the semantic capabilities of ontologies.

An ontology is essentially a specification of entities and their interconnections. In the realm of computer science, ontologies serve as schemas for metadata, offering an organized, machine-readable representation of terms and their relationships. Additionally, they provide a framework for describing a knowledge base populated with individual entities (Kulmanov et al., 2021). By harnessing the power of ontologies, we have developed a fully semantic model tailored to the task of labeling frog images. Our model achieved an overall accuracy of 81%.

Our study concludes that our specialized model outperforms other general models trained on limited data and general-purpose image recognition models, such as DenseNet, in the specific task it was designed for. Our model comprises two integral components: computer vision and ontology, working synergistically to logically infer frog classes based on input images. However, it's important to note that while a purely semantic approach proves invaluable for small-scale applications, it does come with certain drawbacks, such as a limited label pool and reduced accuracy as the scale of the project increases.

The primary objective of this research is to construct a semantic image recognition model and, in the process, gain a deeper understanding of the distinctions between semantic models and traditional mathematical models. Leveraging semantic models to tackle machine learning challenges represents a relatively innovative approach, and ongoing research continues to explore the benefits and limitations of this approach. Our aim is to thoroughly document and analyze the development of this model, shedding light on what can be gleaned from our efforts for future research endeavors in this burgeoning field.

1 Introduction

Machine learning solutions find application across a wide spectrum of fields. However, their effectiveness varies considerably depending on the availability of good, reliable and well-labeled data. The absence of sufficient training data often leads to under performing algorithms plagued by issues such as overfitting and bias. Consequently, certain domains, like bio-informatics, where machine learning could prove beneficial, remain unable to harness its potential due to a scarcity of data, especially for rare diseases (Natarajan et al., 2021). This data scarcity has propelled research in Few-Shot Learning and Zero-Shot Learning, aiming to facilitate learning with limited or even absent data. This study sought to leverage the semantic capabilities of ontologies to mitigate overfitting and bias issues commonly exacerbated by statistical learning methods when operating in low-data environments. Our exploration in this research focused on a novel approach to employ ontologies in image recognition tasks with limited training data.

Our experimentation involved the integration of computer vision and ontological equivalence relationships. The objective was to train a purely semantic model with limited data, free from the characteristic limitations of statistical learning. The experimental process encompassed the initial extraction of information from frog images using computer vision techniques, followed by the application of ontological reasoning to logically deduce the frog's species. Importantly, this approach obviated the need for statistical learning, although the development of the computer vision algorithm and logical axioms in the ontology remained susceptible to overfitting. To mitigate these challenges, we adopted a train/test/validation approach in our training process, fostering the synergy between these two components of the model.

Our results demonstrate that the frog recognition model created through this approach achieves an accuracy of 81%, surpassing classical machine learning models. Moreover, it exhibits superior domain-specific features and accuracy compared to general image detection algorithms. It is important to note that our model outperforms models trained on limited data and excels in the specific task it was designed for when compared to general-purpose algorithms such as DenseNet.

However, we also identified limitations in the purely semantic approach. Complex ontological axioms and the constraints of computer vision hampered our ability to describe certain frogs with available features, necessitating the addition of supplementary features for a more comprehensive description. Additionally, semantic reasoning introduced challenges in handling uncertainty, rendering some predictions more arduous and less reliable.

The main research question for this study is: ”How can semantic models be utilized in place of mathematical models for image recognition tasks with limited data?” Additional sub-questions include:

- How can semantic models be trained without overfitting?
- How can computer vision provide upfront knowledge for semantic reasoning?
- What factors affect accuracy in a semantic model?
- What are the benefits and limitations of using a semantic model?

2 Background and Motivation

2.1 Machine Learning Limitations

Machine learning models, by their very nature, are statistical models whose predictive accuracy is heavily reliant on the quality of the data used during their creation. However, the availability of labeled, high-quality data is not always a given, and the process of annotating enough data for robust learning can be a protracted and daunting task, particularly for smaller teams. Furthermore, because these models operate on statistical foundations, they inherently lack the ability to provide explanations for their decision-making processes (Zanni-Merk & Jeannin-Girardon, 2022). This inherent limitation can lead to scenarios where machine learning models exhibit biased behavior without offering any means to justify or understand why such outcomes occur.

In response to these inherent limitations, we embarked on the development of a semantic-based image recognition algorithm. This approach, centered around the use of axioms and equivalence relationships, considerably diminishes the volume of training data required, rendering it more manageable. Moreover, the ontology-driven approach ensures that the rationale behind each classification becomes transparent and comprehensible. This not only enhances the model's interpretability but also facilitates in-depth analysis of its decision-making processes.

2.2 Ontologies

An ontology is a structured representation of entities and their relationships. In the realm of computer science, ontologies serve as frameworks for organizing and encoding metadata, offering a machine-readable portrayal of terms and their interconnections, as well as a repository for individual entities (Kulmanov et al., 2021). The utilization of ontologies enables the precise delineation of term meanings, extending beyond mere database entries. Due to their myriad advantages, ontology-enhanced learning algorithms have found application in diverse fields, including bio-informatics, finance, and cybersecurity (Natarajan et al., 2021; Yang, 2020; Yeboah-Ofori et al., 2021).

In our context, the ontological structure provides a framework for expressing, accessing, and reasoning with structured knowledge. This aspect of ontologies, known as description logic, comprises two essential components: the TBox and ABox. Within the Description Logic knowledge base, the TBox encompasses knowledge at the class level, while the ABox contains specific instances of individuals (Keet, 2020). By representing knowledge in this structured fashion, automated reasoners can assign inference classes to individual entities. This process empowers automated reasoning over the TBox and ABox. Nevertheless, the seamless integration of ontological structures with machine learning poses a considerable challenge, as it necessitates the a priori definition of knowledge within both the TBox and ABox.

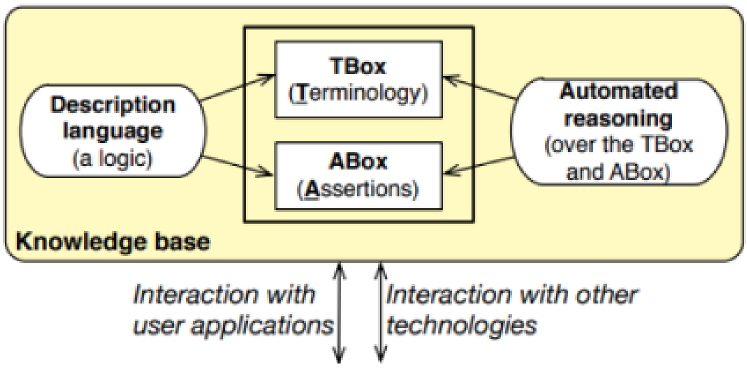

Figure 1: Visual Description of Knowledge Base (Keet,2020)

2.3 Using Ontologies with Machine Learning

Several studies have explored the integration of machine learning with ontologies, opening avenues for enhanced understanding and decision-making at a higher level. Ontologies serve various purposes in reasoning and learning tasks, elucidating the rationale behind machine decisions and injecting prior knowledge into the training process (Kulmanov et al., 2021; Ye et al., 2022). Particularly in the domain of machine learning, ontologies can be employed to restrict the search for optimization solutions, facilitating quicker, improved, and more generalized outcomes (Kulmanov et al., 2021). Furthermore, the ontology-enhanced approach has found utility in few-shot learning, leveraging limited sample spaces for predictive purposes (Ye et al., 2022). Lastly, it holds promise in the realm of Explainable Artificial Intelligence (XAI), as it allows the agent to base its decisions on more than mere statistics, enabling it to offer justifications for its actions, thus enhancing explainability (Zanni-Merk & Jeannin-Girardon, 2022).

The application of ontologies in machine learning can take diverse forms, each with its inherent limitations. Some of these approaches include Ontology Embeddings, which map ontologies into vector spaces, formal language and logic-based methods like Markov logic and probabilistic inference, as well as reinforcement learning as inference (Kulmanov et al., 2021). Past research has demonstrated that the choice of approach to apply ontologies in the learning process varies according to the specific domain. Moreover, the utilization of semantics in learning and the balance between semantics and statistics depend on the task at hand. Hence, we embarked on an exploration of a purely semantic approach to assess the advantages and drawbacks it brings to image recognition tasks within the constraints of limited data settings.

3 Experiment

Our objective was to develop a model for labeling frog images. The fundamental structure of the final model can be summarized as follows. Subsequently, Lastly, validation is conducted using entirely unfamiliar frog images, and the outcomes are meticulously documented.

1. A computer vision component is designed to convert images into detailed descriptions, which are subsequently incorporated into the ABox.

2. An ontology is constructed, leveraging 1-2 training reference images and Wikipedia descriptions to delineate frog classes within the TBox.

3. Testing images are employed to fine-tune hyper-parameters, enhancing the overall performance of both the computer vision and ontology components.

4. Validation is conducted using entirely unfamiliar frog images, and the outcomes are meticulously documented.

3.1 Datasets Used in Experiment

As previously discussed, our experiment was conducted in a limited data environment. While conventional machine learning models typically demand 500-2000 images per class for effective training, our objective was to employ ontologies to facilitate model training with limited data. Regrettably, labeled data pertaining to the subject of our study was not readily available, and the availability of suitable training images was severely constrained. The incorporation of semantics played a pivotal role in rendering the training of our model feasible, and this experiment was conceived to assess its effectiveness.

The model's primary goal is to classify a given image into one of nine distinct frog species. The table below provides an overview of all the species involved and the number of training, testing, and validation images allocated per species. Training images were exclusively utilized as visual references in conjunction with Wikipedia articles to create the semantic foundations for the ontology. Test images served to refine our algorithms, while validation images were deployed to evaluate the final model and had not been previously encountered. Further details on each of these processes will be elaborated on later in this chapter.

Species Name	Training Photos	Testing Photos	Validation Photos
Amazon Milk Frog	1	2	10
Argentine Horned Frog	2	2	12
Blue Poison Dart Frog	1	2	10
Northern Leopard Frog	2	2	12
Red Eyed Tree Frog	1	2	10
Striped Marsh Frog	2	2	11
Tomato Frog	1	2	10
Yellow Banded Poison Dart Frog	1	2	10

Table 1: Dataset Details

3.2 Model Outline

In order to get around the constraints imposed by limited data, our approach employs a distinct model that seeks to semantically infer object identities based on readily detectable visual attributes common to all frog species. Our model comprises two key components. The first component involves computer vision, focusing on the identification of visual attributes and the creation of object descriptions based on these attributes. The second component is the ontology, which employs logical reasoning to deduce the type of object that corresponds to the provided description.

The fundamental workflow of our model involves the initial extraction of image features through computer vision. Subsequently, the results are stored as individuals within an ontology file, wherein the desired labels are represented as classes. Lastly, we utilize the HermiT reasoner to make inferences regarding the object names using the ontology definitions. The computer vision algorithms, in conjunction with the ontological framework, constitute our model, and they are developed through a process involving training, testing, and validation. Together, these components generate the ABox and TBox of the ontology, enabling automated reasoning.

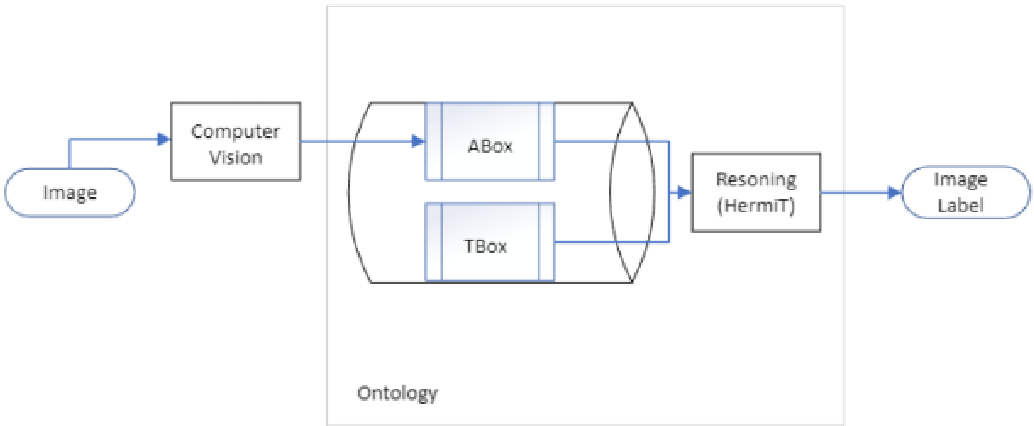

Figure 2: Visual description of the model

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3.2.1 Computer Vision

Computer vision plays a pivotal role in systematically extracting visual features from images. The Python library open-CV is utilized for implementing computer vision solutions. Connected component extraction, convolution edge deduction provided by this library is used to extract visual attributes from images. In this experiment, the selected visual attributes are the body, dots, and stripes, along with the inclusion of up to two colors for the body and one color for all the dots. The choice of features at this stage significantly influences the capabilities and constraints of the equivalence relationships within the ontology, consequently impacting the overall algorithm's accuracy.

Furthermore, to refine the computer vision algorithms, it becomes imperative to fine-tune hyper-parameters. This fine-tuning process is executed through a three-step procedure known as train/test/validation, which will be discussed in greater detail later in this chapter.

3.2.2 Ontology Structure

Our ontology is structured into two fundamental components. First, it comprises classes and object properties, which form the foundational elements essential for semantic reasoning. Second, it encompasses individuals, which represent images translated into objects within the ontology database. The classes encompass various frog types and specific body parts constituting these frogs. The frog classes are integral to our reasoning capabilities, representing the model's options for making predictions based on a given image. Logical connections between frogs and body parts are established using the "hasPart" function, defined from frogs to animal parts. This connection is realized by establishing equivalence relationships for each frog, describing it in terms of the animal parts it possesses. As an example, a class within the ontology description might be the "yellow-banded poison dart frog," which is equivalent to "hasPart some yellow body and hasPart some black body."

There are three primary categories of body parts: body, dot, and stripe, along with options for colors. Stripe color and dot detection are handled by the computer vision component. This structural design enables the model to recognize similar features and generate equivalent relationships for all target labels. However, it's essential to acknowledge that each frog description can vary in complexity, a subject that will be further explored in this chapter.

3.3 Model Creation Steps

To mitigate the risk of overfitting, we have adapted the machine learning paradigm of training, testing, and validation into our model creation process. The train, test, and validation approach is employed to prevent the development of models biased toward the dataset used during the creation phase. Such bias could result in models exhibiting much higher accuracy during development compared to their performance in real-world scenarios. Although this model doesn't require training in the conventional sense, it is crucial to strike a balance between expressiveness and simplicity without succumbing to overfitting. Therefore, we have adopted this three-step process to ensure that the model's structure remains robust without introducing excessive noise into the resulting CSV file and reducing the likelihood of false positives.

3.3.1 Training

The training phase involves the development of computer vision algorithms and ontology equivalence relationships to facilitate the inference of frog species based on visual attributes. Initially, it is essential to determine which features can be systematically used to distinguish between different classes. In our specific case, the features include body color, the presence of stripes, and the color or presence of dots.

Subsequently, each frog is characterized based on images, establishing equivalence relationships within the ontological structures discussed earlier. This segment entails manual adjustments of ontology descriptions and algorithms to align them with the training image set. To summarize, the training phase encompasses the creation of the ABox and TBox components of the ontology that will be employed for reasoning. The TBox is directly created, while images are transformed into ABox individuals through the application of computer vision.

3.3.2 Testing

In this phase, the computer vision algorithm and semantic reasoning are evaluated using a new set of images. These images serve to identify cases that lead to false positives and recognize which features are frequently absent from the computer vision analysis. Detecting these errors can be challenging when testing on a more extensive and diverse dataset. Two strategies are employed to enhance our model: simplifying redundant logical equivalences and introducing alternative logical equivalences. For instance, in our model, we removed the presence of stripes from the equivalence relationship of some classes, as identifying two distinct colors proved consistently sufficient. Additionally, we included additional descriptions for the Argentine Horned Frog, as their stripes are at times quite small and may appear as dots. This phase also entails the fine-tuning of model hyperparameters. In our case, as previously discussed, hyperparameters for dot and stripe detection are adjusted to optimize performance in the testing environment.

3.3.3 Validation and Output

Similar to standard machine learning procedures, unseen images are employed in the validation phase to assess the model's accuracy and its ability to generalize. In our case, we utilized 85 previously unseen images for validation, and the model accurately classified 69 of them. The final output, encompassing all translated visual features for images, is stored in a CSV file. Subsequently, this CSV file is processed by the ontology as individuals using a Python script. Finally, the HermiT reasoner and the Protégé tool are employed to obtain inferred classes for all frog species. A summary of all ontology classes, along with the number of correct and false predictions per class, is provided in the table below.

Species Name	Ontological Description	Total	Correct	Accuracy
Amazon Milk Frog	(hasPart some BlackBody) and (hasPart some WhiteBody)	10	8	80%
Argentine Horned Frog	((hasPart some BlackBody) or (hasPart some BrownBody)) and (hasPart some GreenBody) and (hasPart some Striped)	12	10	83.3%
Blue Poison Dart Frog	(hasPart some BlackDot) and (hasPart some BlueBody)	10	9	90%
Northern Leopard Frog	(hasPart some BlackDot) and (hasPart some GreenBody) or (hasPart some BlackDot) and (hasPart some BrownBody)	12	8	66.7%
Red Eyed Tree Frog	(hasPart some BlueBody) and (hasPart some GreenBody) and (hasPart some Striped)	10	9	90%
Striped Marsh Frog	(hasPart some BlackBody) and (hasPart some BrownBody)	11	7	63.7%
Tomato Frog	hasPart some RedBody	10	10	100%
Yellow Banded Poison Dart Frog	(hasPart some BlackBody) and (hasPart some YellowBody)	10	9	90%

Table 2: Validation Results

4 Results

4.1 Accuracy Evaluation

As previously highlighted, this model significantly differs from statistical processes, and thus, the causes of low accuracy diverge from those of a typical machine learning model. While the accuracy of machine learning hinges on the quality and quantity of data available, this model's accuracy is primarily contingent on the quality of equivalence relationships and the computer vision's capability to report accurately. Firstly, the ontology must be meticulously constructed and should not draw incorrect deductions when provided with accurate data. Developing a robust ontology for our specific task becomes a delicate balance between simplicity and expressiveness, considering that the computer vision component may not consistently detect correct features.

Secondly, computer vision may occasionally falter, either reporting extra features or omitting crucial features entirely. This can result in objects being misidentified as other objects and is closely tied to the quality of equivalence relationships. Some objects may bear a striking resemblance to others, necessitating elaborate and specific descriptions. Consequently, minor mistakes in feature detection could lead to errors. Conversely, certain objects, like the Tomato frog, require only a red body for accurate identification, resulting in high accuracy. However, such simple descriptions are only feasible when there are no other red-bodied frogs among the target objects. To sum up, simplistic descriptions offer more room for error in feature detection, while expressive descriptions permit the detection of complex and similar objects within a broader pool of potential objects. Detailed accuracy and logical equivalence information for each frog species can be found in the table below.

4.1.1 Comparison with models trained on low data

For comparative purposes, we trained a conventional machine learning model designed to identify two visually similar frog species: the Argentine frog and the Leopard frog. This specific task aligns with our model's strengths. Due to time constraints and the scarcity of labeled images for our objective, we opted for a less sophisticated model. The competing model was also trained on a limited dataset, a known factor that can significantly reduce the accuracy of machine learning models. The model was trained using classical machine learning techniques and the ImgAI library, achieving a 66% accuracy rate. In contrast, our model exhibited an average accuracy of 81% using the same validation data for these two frog species. Consequently, our model proves to be a suitable candidate for addressing limited data scenarios in Few-Shot Learning (FSL) and Zero-Shot Learning (ZSL), especially when dealing with challenging and demanding tasks.

4.1.2 Comparison with Comparison with DenseNet

DenseNet is an image detection algorithm developed by Facebook, trained on a vast dataset comprising over a thousand images. Although undoubtedly feature-rich for typical use cases, we aimed to assess its performance in specific scenarios, such as our frog detection algorithm. The test was conducted exclusively with Tree Frogs, as these were the only frog species our model was trained to identify among the three detected by DenseNet.

Our model exhibited two major advantages during these tests. Firstly, our model demonstrates a broader range of frog detection capabilities and is highly customizable, while DenseNet can only identify three species. Secondly, our model outperformed DenseNet in terms of accuracy in its area of specialization. For Tree Frogs, DenseNet correctly identified 80% of the cases, whereas our algorithm achieved a 90% accuracy rate. Moreover, DenseNet produced more false positives. Therefore, our model proves to be well-suited for designing specialized image recognition algorithms for small groups and specific use cases.

4.2 Limitations and Possibilities

While we achieved commendable accuracy with limited data, two major limitations emerged in the process: limited label space and restricted prediction capabilities. These limitations influence the range of objects that can be accurately labeled from images and the precision of these labels. Addressing and comprehending these challenges can illuminate the path for future research and advancements in this domain.

4.2.1 Limited Label Space

During the development of our model, we encountered the challenge of accommodating certain frog types, as describing them within our feature space proved infeasible. Additionally, some exceptionally straightforward frogs posed limitations on our ability to include them in the ontology. Firstly, certain frog descriptions would require specific, one-of-a-kind features to be detected by the computer vision algorithm. For instance, a bullfrog possesses a predominantly uniform green body with no distinguishing features except for eardrums. While most frogs exhibit dots and stripes, eardrums are exceedingly rare, and introducing this feature for detection by the computer vision algorithm could result in numerous false positives. Moreover, adding this feature would be time-consuming and intricate, with limited benefits. The reason for this complexity lies in the fact that the sole differentiation between a dot and an eardrum is the texture of their surface. Under computer vision, eardrums would appear identical to dots, much like how some eyes are detected as dots. Consequently, the inclusion of numerous features proved unattainable and constrained the variety of frogs we could label.

Secondly, some frogs had very simplistic descriptions in our model, such as the tomato frog, as discussed earlier. These frogs exhibited exceptional accuracy within our model. However, adding another red-bodied frog would necessitate altering the description for the tomato frog. This poses challenges because the tomato frog lacks distinguishing features beyond its red body, making the description inherently uncomplicated. Altering the description to label frogs with solely a red-body feature as tomato frogs might function but would not account for variations among these frogs, including the presence or absence of dots. Furthermore, this alteration could diminish the accuracy of all red-bodied frogs, akin to how many green-bodied frogs exhibit below-average accuracy. Consequently, our approach struggles to label a substantial number of frogs without compromising accuracy and introducing considerable complexity and labor intensiveness into the algorithms.

4.2.2 Limited Prediction Capabilities

Most machine learning algorithms can provide multiple labels with varying levels of certainty when presented with a problem. In essence, a machine learning model is grounded in mathematical formulas and can assign probabilities to each of its predictions based on these mathematical underpinnings. In contrast, semantic ontological learning operates differently. It necessitates the upfront definition of knowledge, and inferences drawn from this knowledge are deterministic. This presents challenges since current technology cannot automatically provide entirely correct data upfront based on images. Consequently, models will make incorrect predictions due to the inherent flaws in computer vision algorithms. Furthermore, as all knowledge provided to the model is treated as certain and equal, predictions cannot be ranked by probability, as they are considered equally valid in the ontology's perspective. Finally, a correctly constructed ontology cannot offer more than one prediction, as two objects described as classes are logically disjoint sets, meaning that an individual cannot simultaneously belong to both. For instance, an Argentine frog cannot be a leopard frog at the same time, even if one desires to provide both as label guesses for an individual. This would result in a reasoner error. Therefore, using ontologies for the purpose of labeling images introduces several limitations.

5 Conclusion

This study explored the application of semantic models. We have demonstrated that incorporating semantics into learning can yield benefits, particularly in terms of explainability and enhanced accuracy in limited data scenarios. However, it appears that for each advantage that semantic learning offers, it also carries a significant drawback that restricts its application in larger-scale contexts. Consequently, we propose the integration of semantic learning into machine learning models, as opposed to using it in isolation. Although this approach is more complex than using semantic models independently, our findings underscore the potential areas within machine learning models that can benefit from the utilization of ontologies.

6 Future Work

Future work includes improving the accuracy of semantic models by enhancing the ontology's equivalence relationships, exploring the use of more advanced computer vision techniques, and investigating ways to overcome limitations related to scale and label pool size. Additionally, studying the efficiency of combining semantic and mathematical models in hybrid systems for image recognition tasks is an interesting frontier for further research. As the field of semantic web technologies continues to evolve, and with the emergence of new laws and regulations governing machine learning, we believe that explainability ontologies could be the next major advancement in the realm of machine learning. This integration has the potential to facilitate the creation of models with reduced data requirements, making these algorithms accessible to a broader audience, and ultimately benefiting a wider range of individuals.

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