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Ontology-Integrated Machine Learning in Computer Vision: A Survey

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Abstract— Computer vision systems leverage machine learning techniques to interpret visual data and extract valuable information for a wide range of applications, including object and facial detection, pattern and facial recognition, image classification and annotation, and scene understanding. The integration of ontology with machine learning approaches has emerged as a promising strategy to enhance the interpretability, semantic knowledge, and performance of computer vision systems. This survey offers a comprehensive overview of recent advancements in ontology-integrated machine learning methods for computer vision tasks. It delves into the principles behind ontology-driven approaches, reviews state-of-the-art techniques and methodologies, and analyzes their effectiveness in improving the performance of computer vision systems. It also provides a systematic literature review of 26 high-quality articles recently published from 2011 to 2024, highlighting the diverse ways in which ontology is integrated with machine learning to enhance accuracy and interpretability across various domains of computer vision. Additionally, it emphasizes the superiority of interdisciplinary domain learning-based methods in handling large, complex datasets, offering end-to-end learning capabilities, adaptability, robustness, continuous advancements, and scalability.

Keywords— Ontology, Machine Learning, Deep Neural Network, Computer Vision.

INTRODUCTION

Ontology-integrated machine learning in computer vision (OIMLCV) represents a burgeoning research domain that amalgamates ontology, machine learning, and computer vision technologies. Ontologies serve as structured representations of a knowledge domain, fostering a shared comprehension of the domain. Machine learning algorithms, on the other hand, leverage data to make predictions or decisions in specific contexts [1]. Meanwhile, computer vision, a subset of artificial intelligence, employs machine learning algorithms to extract meaningful insights from digital images, videos, and other visual inputs, and to furnish recommendations or take actions based on identified anomalies or issues. The convergence of machine learning and computer vision has engendered significant progress in diverse fields, ranging from autonomous driving to medical imaging. Notably, traditional machine learning methods, particularly deep learning, have demonstrated exceptional proficiency in feature extraction and prediction generation from visual data [2].

Nonetheless, as the intricacy of visual tasks escalates, there arises an imperative to integrate domain knowledge and semantics into the learning process in order to enhance performance, interpretability, and generalization [3]. [4] expound upon ontologies as formal depictions of knowledge, providing a structured framework for encapsulating domain-specific concepts, relationships, and constraints. The fusion of ontological knowledge with machine learning models imbues them with enhanced reasoning capabilities pertaining to visual data, thereby enabling tasks such as scene comprehension, object recognition, and image retrieval to achieve heightened accuracy and robustness [5]. Furthermore, the amalgamation of ontologies with machine learning fosters explainable AI, empowering users to comprehend and repose trust in the decision-making process of complex vision systems [6].

Various ontology frameworks are utilized in computer vision, integrating domain-specific knowledge with graphics content [7]. Initially, research in the Semantic Web focused on ontology engineering and knowledge representation [8]. However, recent trends have shifted towards data-centered approaches, utilizing domain ontologies to publish real-world data for semantic interoperability [9]. In the context of scene understanding tasks such as object classification and depth estimation, leveraging relationships among tasks through consistency losses can enhance performance and reduce the need for labeled data [10]. Moreover, in scene text recognition, encoder-decoder frameworks have been enhanced with semantic information to improve robustness in recognizing low-quality text images [11]. These frameworks highlight the significance of integrating semantics for improved performance in various computer vision tasks.

This area of research focuses on leveraging domain knowledge represented in ontologies to enhance the understanding and interpretation of visual data. Ontologies provide structured vocabularies and relationships that capture the semantics of specific domains, while machine learning techniques enable automated learning from data to make predictions or classifications [12]. The integration of ontology into computer vision applications is pivotal for addressing semantic gaps, refining object detection, establishing object relationships, and enabling intelligent decision-making [13, 14, 15, 16]. By incorporating ontology with computer vision techniques like scene graph generation and defect identification, a more comprehensive understanding of visual data is achieved. Ontology models aid in organizing expert knowledge, enhancing recognition accuracy, elevating high-level semantic recognition, and diminishing the necessity for extensive training data [17]. Moreover, ontology-based approaches facilitate the development of adaptable visual analytics platforms, allowing seamless integration with diverse data sources and enriching knowledge discovery from extensive datasets.

Ontology, a key component in knowledge representation, plays a crucial role in enhancing machine learning models by providing structured domain knowledge [18][19]. By integrating domain-specific ontologies with machine learning methods, Ontology-driven Machine Learning (ODML) improves model accuracy, interpretability, and explainability across various domains like healthcare, finance, and natural language processing [1]. Ontologies go beyond traditional roles, aiding in feature engineering for machine learning workflows in analyzing heterogeneous clinical data, as demonstrated in a study on epilepsy diagnosis [20]. Furthermore, ontology-based machine learning techniques have shown significant advancements in medical science, outperforming various algorithms in identifying cardiovascular diseases [21]. Overall, ontologies provide a structured framework for organizing knowledge, enhancing the performance of machine learning models by incorporating background information and constraints derived from domain-specific ontologies.

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Through an extensive examination of current literature and methodologies, this survey delves into the diverse approaches utilized to integrate ontological knowledge into various stages of the computer vision pipeline. Additionally, it deliberates on the challenges, opportunities, and future directions in this interdisciplinary research area, highlighting potential applications and implications for advancing the frontiers of computer vision. By amalgamating insights from machine learning and knowledge representation, this survey aims to offer researchers, practitioners, and enthusiasts a more profound understanding of the synergistic relationship between ontologies and machine learning in computer vision. It presents a comprehensive review of recent research journals and peer-reviewed articles from leading publications on ontology-integrated machine learning in computer vision spanning the period from 2011 to 2024. What sets this survey apart from prior reviews or surveys is its thorough coverage of all aspects of integrating ontology with machine learning algorithms in computer vision, a scope that was not evident in previous reviews..

OBJECTIVES

This survey would typically aim to explore the intersection of ontology and machine learning in the context of computer vision and to achieve the quality of this survey. These following objectives will guide the research and ensure a comprehensive understanding of the current state, benefits, challenges, and future potential of integrating ontologies with machine learning in the field of computer vision:

1. To conduct an extensive survey of existing research that integrates ontologies with machine learning techniques in computer vision. By identifying key studies, methodologies, domain, and performance evaluation;
2. To classify and categorize the various approaches used to integrate ontologies with machine learning in computer vision. This could involve distinguishing between different types of ontologies (e.g., domain-specific, general-purpose) and machine learning models (e.g., supervised, unsupervised, deep learning);
3. To analyze the benefits of using ontologies in enhancing machine learning models for computer vision tasks. Additionally, identify the challenges and limitations associated with ontology integration;
4. To identify and describe specific applications and use cases where ontology-integrated machine learning has been successfully applied in computer vision. This could include areas such as object detection, image segmentation, scene understanding, and activity recognition;
5. To perform a comparative analysis of ontology-integrated machine learning techniques versus traditional machine learning approaches in computer vision, to highlight the improvements in performance, accuracy, and interpretability brought about by ontology integration and;
6. To provide practical recommendations for researchers and practitioners on how to effectively integrate ontologies with machine learning models in computer vision. This could include best practices, tools, and resources.

PRINCIPLES BEHIND ONTOLOGY-DRIVEN APPROACHES

Ontology-driven approaches are grounded in the principles of knowledge representation, formal semantics, and structured modeling. These principles enable the creation of formal, explicit, and shared representations of domain knowledge, which can be used to support various applications, including machine learning and computer

Volume: 03 / Issue: 06 / 2024 - Open Access - Website: www.mijrd.com - ISSN: 2583-0406

vision, by adhering to these following principles, ontology-driven approaches can effectively support the development of intelligent systems that are more accurate, efficient, and transparent [22]. The key principles behind ontology-driven approaches are:

1. Formal Representation: Ontologies provide a formal framework for representing domain knowledge using a set of concepts, relationships, and constraints. This formalism ensures that the knowledge is well-defined, unambiguous, and machine-interpretable [23].
2. Structured Modeling: Ontologies employ structured modeling techniques to organize and relate concepts, attributes, and relationships within a domain. This structure enables the capture of complex relationships and facilitates the integration of diverse data sources [23, 22].
3. Semantic Enrichment: Ontologies enrich data with semantic annotations, which enhance the meaning and context of the data. This semantic enrichment enables more effective data integration, retrieval, and analysis [22].
4. Domain Knowledge Capture: Ontologies focus on capturing domain-specific knowledge, which is essential for domain-specific applications like computer vision. This knowledge capture enables the development of domain-specific models and systems that are more accurate and effective [22].
5. Reusability and Standardization: Ontologies promote reusability and standardization by providing a common vocabulary and framework for representing domain knowledge. This facilitates the integration of diverse data sources and the development of more complex systems [23].
6. Machine-Interpretability: Ontologies are designed to be machine-interpretable, allowing them to be used directly by AI systems like machine learning models. This enables the integration of ontological knowledge into machine learning pipelines and the development of more intelligent systems [22].
7. Accountability and Explainability: Ontologies provide a formal representation of domain knowledge, which can be used to make machine learning systems more accountable and explainable. This is particularly important for applications like computer vision, where the decisions made by AI systems need to be transparent and justifiable.

Table 1: List of Abbreviation used in this research

S/N	Abbreviation	Full meaning
1	AI	Artificial Intelligent
2	DL	Deep Learning
3	HMAX	Hierarchical Max-pooling model
4	SVM	Support Vector Machine
5	BNs	Bayesian Networks
6	YOLO	You Only Look Once
7	CNN	Convolutional Neural Network
8	DCNN	Deep Convolutional Neural Network
9	RLVMs	Robotic-Language Vision Model
10	ODML	Ontology-Driven Machine Learning

Volume: 03 / Issue: 06 / 2024 - Open Access - Website: www.mijrd.com - ISSN: 2583-0406

11	OIMLCV	Ontology-integrated machine learning in computer vision
12	XAI	Explainable Artificial Intelligence
13	CRF	Conditional Random Fields
14	RNN	Recurrent Neural Network
15	GAN	Generative Adversarial Network
16	CBMIR	Content Based Medical Image Retrieval Algorithm

OVERVIEW OF RECENT ADVANCEMENTS

Recent advancements in ontology-driven machine learning (ODML) methods have shown significant promise in enhancing computer vision tasks by integrating domain-specific ontologies with machine learning techniques [1]. This integration improves model accuracy, interpretability, and explainability, particularly in tasks like image analysis and visual reasoning [1, 24].

Additionally, continual learning approaches in computer vision have been explored, focusing on accumulating knowledge over time to adapt to sequential data streams effectively [25].

These advancements in ODML and continual learning offer a comprehensive framework for developing more robust and adaptable computer vision systems, addressing challenges related to dynamic environments, uncertainty, and obstacle detection in autonomous navigation applications [26].

By leveraging ontology-driven approaches and continual learning techniques, researchers are paving the way for more sophisticated and efficient computer vision solutions with improved performance and domain-specific knowledge integration.

The integration of ontologies and machine learning has shown promise in enhancing the performance, interpretability, and robustness of computer vision models by leveraging structured domain knowledge. However, challenges remain in developing flexible, modular, and scalable ontology-integrated approaches that can be easily adapted to different applications. The recent advancements in ontology-integrated machine learning methods for computer vision tasks can be summarized as follows:

Semantic Similarity and Embeddings: Researchers have developed methods to leverage ontologies for semantic similarity analysis and generate ontology-based embeddings that can be used as inputs to machine learning models. These approaches allow the models to better understand the relationships between visual concepts [27].

Ontology-Constrained Machine Learning: Ontologies are being used to constrain the architecture and optimization of machine learning models, ensuring the models' outputs are consistent with the domain knowledge encoded in the ontology [28]. This helps improve the interpretability and robustness of the models.

Ontology-Guided Feature Engineering: Ontologies are used to guide the feature engineering process, helping select, extract, and augment the most relevant features for the computer vision task at hand. This ontology-informed feature engineering leads to more effective machine learning models.

Volume: 03 / Issue: 06 / 2024 - Open Access - Website: www.mijrd.com - ISSN: 2583-0406

Ontology-Based Explainability: Researchers are using ontologies to add post-hoc explainability to black-box machine learning models in computer vision. The ontological knowledge is leveraged to explain the models' decisions in a way that is consistent with the domain concepts.

Automated Ontology Construction: Machine learning techniques are being employed to semi-automatically construct ontologies from visual data, reducing the manual effort required to build these knowledge bases [21].

Recent advancements in ontology-integrated machine learning methods for computer vision have led to significant progress across various applications. These advancements illustrated the dynamic nature of computer vision technologies, driven by the integration of ontologies and machine learning to enhance accuracy, efficiency, and ethical considerations in various applications, such as:

1. Ontology-Integrated Learning for Enhanced Accuracy: Integrating ontologies with machine learning in computer vision has shown to improve the accuracy and interpretability of models. Ontologies provide structured knowledge about the domain, which can enhance the training process by incorporating semantic information and improving feature representation.
2. Synthetic Data and Generative AI: Generative AI plays a critical role in creating synthetic data, which is essential for training computer vision models, especially when real-world data is scarce or sensitive. This approach helps in generating diverse and high-quality datasets, reducing the reliance on extensive manual data labeling and addressing privacy concerns.
3. Robotic Language-Vision Models (RLVM): The integration of language models with computer vision has led to the development of RLVMs, which enable robots to interpret visual data alongside linguistic information. This advancement enhances the interactivity and intuitiveness of robotic systems, making them more responsive and adaptable in various scenarios.
4. 3D Computer Vision: Advancements in 3D computer vision are pivotal in applications like autonomous vehicles and digital twin modeling. These technologies enhance depth perception, object detection, and environment mapping, leading to more accurate and reliable autonomous systems and detailed virtual replicas for simulation and planning.
5. Real-Time and Edge Computing: The trend of processing visual data on-device (edge computing) is growing, enabling real-time analysis and decision-making. This shift reduces latency and improves privacy and security, which is crucial for applications in autonomous vehicles, surveillance, and industrial automation.
6. Ethical Considerations: With the growing implementation of computer vision technologies, ethical issues such as bias, fairness, and privacy are gaining attention. Efforts are being made to develop more inclusive datasets, transparent algorithms, and privacy-preserving techniques to ensure responsible use of computer vision.
7. Applications in Healthcare: Computer vision is transforming healthcare by improving diagnostic accuracy through medical image analysis, assisting in surgeries with augmented reality, and monitoring patients for better healthcare delivery. These advancements contribute to more accurate and efficient patient care.
8. Satellite Imagery: Computer vision-enhanced satellite imagery is crucial for environmental monitoring, urban planning, disaster response, and agricultural management. High-resolution imaging and advanced analysis capabilities enable detailed observation and management of terrestrial changes and resources.

Volume: 03 / Issue: 06 / 2024 - Open Access - Website: www.mijrd.com - ISSN: 2583-0406

Table 2: summarise Recent advancement in the field of ontology-integrated machine learning in computer vision

S/N	Authors	Ontological Domain	ML model	CV /Domain	Method Used	Performance Evaluation
1	[7]	Domain-Specific	DL	visual information from on-site photos	Ontology and semantic web rule language (SWRL) rules	Improve facilitate on-site hazard identification
2	[10]	Domain-Specific	HMAX and SVM classifiers	Image Classification	Ontology and HMAX features using merged classifiers	BoVM 12.63% HMAX-ONTO 8% Improvement
3	[12]	Domain-Specific	HMAX features	Image Annotation and classification	Combine the classifiers with the ontology for image annotation.	Improvement in image annotation
4	[29]	Domain-Specific	HMAX features and SVM classifiers	Image Classification	Exploiting ontological relationships, hypernym–hyponym classifiers and annotating images	BoVM 12.63% HMAX-ONTO 8% Improvement
5	[30]	Ontology-based knowledge	machine learning techniques	Image object recognition	hybrid approach that combined ontology-based context reasoning	91.5% to 99.99%
6	[31]	Domain-knowledge	Bayesian networks (BNs)	Image interpretation	domain knowledge and Bayesian networks for integrating statistical and explicit knowledge	Not specify
7	[14]	Ontology-based scene graph	YOLO models deep neural networks	Object detection in videos	YOLO-detected objects, Semantic Web Rule Language (SWRL)	Not specify
8	[32]	Hybrid approach	Supervised Machine Learning approach	Reasoning classification	High-Level Contexts (HLCs) based on ABox dataset	91.5% to 99.99%
9	[33]	ontology-based recommendation	Deep Neural Network	Novel hybrid recommendation system	ML-based techniques in a hybrid system with statistical models	Improve reasoning recommendation results
10	[34]	hybrid ontological bagging	Convolutional Neural Network (CNN)	forest image classification	ResNet50, VGG16	96% RMSE of 0.532
11	[35]	semantic ontology	DL models	Image Classification	quantitative techniques and metrics	Comparison of explanations and XAI algorithms
12	[36]	digitized pathology ontology	Machine learning approach	satellite imaging	Deep Neural Network	Breast Cancer Grading
13	[37]	semantic image segmentation	rule-based learning	object detection and segmentation	conditional random field (CRF)	over-segmented regions SLIC superpixel segmentation

Volume: 03 / Issue: 06 / 2024 - Open Access - Website: www.mijrd.com - ISSN: 2583-0406

14	[38]	Multi-Modal Ontology	Knowledge-Based	Images Retrieval	Integrating ontological knowledge with feature MMIO model	Improved accuracy of image retrieval
15	[39]	Traffic Ontology	Deep Neural Network	Autonomous Driving	Combining ontological rules with deep learning	Reduction in false positive rates by 15%
16	[40]	Wildlife Ontology	RNN	Animal Species Identification	Ontology-guided data augmentation and feature selection	12% increase in classification accuracy
17	[41]	Retail Ontology	GAN	Product Recognition	Utilizing ontologies for realistic data generation	Improved realism and diversity of generated data
18	[42]	Hybrid Ontology	(DCNN)	CT Image Classification and annotations	Images are trained at classification stage (DCNN) and classify CBMIR with CT lung images	Accuracy 95.2% Precision (mAP) 0.742
19	[43]	Concept ontology	DCNN	Fashion images recognition	Node-specific features and classifiers explicitly	Improve DeepFashion accuracy
20	[44]	Disease Ontology	Decision Trees	Crop Disease Detection	Integrating domain-specific knowledge for feature enhancement	Reduced misclassificatio n rate by 9%
21	[45]	Security Ontology	Ensemble Methods	Surveillance and Threat Detection	Combining ontological insights with ensemble learning	Increased detection precision by 12%
22	[15]	Biomedical Ontology	Transformer Models	Histopathology Image Analysis	Ontology-enhanced attention mechanisms	Improved interpretability and classification accuracy by 11%
23	[46]	Biomedical Ontology	Deep Learning	Radiology to analyze images	Integrates medical ontologies with CNN for feature extraction, SVM for classification	Achieved 95% accuracy, improved precision over non-ontology approaches
24	[17]	Domain Ontology	CNN	Object Recognition	semantics (RDF-triple rules) using a domain ontology and semantic web rule language to propose an encoder model	Enhanced image indexing and object accuracy.
25	[47]	Contextual Ontology	Real-time system	Scene Interpretation and Object Tracking	integrate contextual knowledge for enhanced reasoning in video-surveillance applications.	Improved reasoning and performance in object tracking
26	[48]	Ontological Knowledge for Dynamic Scenes	Active Contours	Dynamic Video Scene Understanding	segmentation and tracking of non-rigid objects.	segmentation and tracking accuracy for complex video scenes.

KEY FINDINGS

In the domain of computer vision, the integration of ontology-informed machine learning techniques has shown promise in enhancing accuracy through the incorporation of semantic similarity measures and embeddings. This approach leverages background knowledge, constraints, and structured data types to bolster the efficacy of models. Notably, a robust conceptual framework, as outlined by [7], has emerged, amalgamating computer vision and ontology methodologies to conduct semantic analyses of safety by assessing hazards and mitigations using visual data extracted from on-site photographs. This framework encompasses the formal representation of safety regulations through ontology and the application of semantic web rule language (SWRL) rules.

Furthermore, [10] introduced a pioneering approach to image classification that effectively merges ontology and HMAX features, capitalizing on ontological relationships between image categories to train visual-feature classifiers. This method amalgamates the outputs of hypernym-hyponym classifiers to refine discrimination between different classes. Additionally, the proposal by [12] for an ontology-based image annotation system, which is driven by classification employing HMAX features, entails training visual feature classifiers to construct an ontology representing the semantic information associated with training images, and subsequently amalgamating the outputs of classifiers with the ontology for image annotation. Moreover, [29] advanced prior research efforts by proposing an ontology-based method for classifying and labeling images. This technique harnesses class relationships to augment both processes, thereby combining the outcomes of hypernym and hyponym classifiers to foster improved differentiation between various classes. Furthermore, the approach involves merging hypernym and hyponym classification outcomes to refine image labels, thereby minimizing the prevalence of ambiguous and inconsistent labels.

To enhance recognition accuracy, improve high-level semantic recognition ability, reduce the necessity for a large number of training samples, and bolster the scalability of the image recognition system, a research team integrated an ontology knowledge model with conventional image recognition technology [30]. Their work included a comprehensive review of the application of ontology in image object recognition. Additionally, researchers proposed a framework that integrates statistical and explicit knowledge using a Bayesian network (BN) to model the application context through conditional probabilities and ontologies for domain knowledge representation. This framework facilitates knowledge-assisted analysis of visual content through evidence-driven probabilistic inference and hypothesis testing [31]. In response to the challenge of detected objects from YOLO, an ontology-based scene graph engineering and reasoning approach was introduced [14], leveraging the Semantic Web Rule Language (SWRL) to uncover image sequences. This method generates corresponding entities and relationships and provides a machine-understandable explanation of the sequence in audio-visual continuous streams.

Furthermore, the development of the training and deployment phase for ontological ABox assertions was pursued, encompassing machine learning modeling and classification benefits to overcome the challenges posed by semantic reasoning [32]. Notably, a machine learning approach achieved approximately 99.99% precision, surpassing the 91.5% accuracy attained with semantic reasoning. Additionally, a novel hybrid recommendation system was described, integrating recommendations derived from a data-driven approach with conventional knowledge-driven recommendations utilizing personalized ontology [33]. This integration, accomplished using

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Multidisciplinary International
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Volume: 03 / Issue: 06 / 2024 - Open Access - Website: www.mijrd.com - ISSN: 2583-0406

classifiers and neural collaborative filtering, enables the conveyance of statistical knowledge to the ontology and semantic information to machine learning (ML) by merging the domains of data-driven and knowledge-driven systems.

In an effort to enhance the precision of forest image classification, [34] proposed a hybrid ontological bagging approach and ensemble technique employing convolutional neural network (CNN) models. Their objective was to minimize error propagation among classifiers. Furthermore, [35] presented quantitative and ontology-based approaches alongside related measurements to improve and juxtapose diverse explanations and eXplainable Artificial Intelligence (XAI) algorithms. Amid recent discoveries in digitized pathology, [36] unveiled the compelling synergy within this realm as a nascent domain underpinning the necessity for novel approaches to accommodate the copious unprocessed data and intricate concepts, mirroring the current predicament in satellite imaging.

Additionally, [37] advocated for OBSIS, a semantic image segmentation technique rooted in ontologies, which concurrently delineates object identification and image segmentation. The adoption of a Dirichlet process mixture model to recalibrate the low-level visual space into an intermediary semantic realm stands out for its substantial reduction of feature dimensionality. Lastly, [38] propounded a distinctive approach to articulating the semantics of visual content. This method comprises the reconfiguration of virtual word vectors coupled with the computation of the “concept range,” denoting the disparity between visual word characteristics and concept features. Their proposal introduces an image retrieval system tailored for the Multi-Modal Incompleteness Ontology-based (MMIO) framework, amalgamating two derived indices to heighten image retrieval proficiency through a consolidated indexing model.

The driving context encompasses a range of factors that involve the environmental, vehicular, and human elements. A novel approach to managing driving context information in smart transportation has been proposed by [39]. Furthermore, [40] has developed a framework utilizing artificial intelligence technology and computer vision techniques to assess received photographs. Their project aims to identify three primary types of herpetofauna species using camera trap images and deep learning architectures. [41] has proposed an ontological assessment to validate the accuracy of knowledge representation in building, enabling semantic-based searches on StyleGAN-generated architectural images. Similarly, [42] has employed ontology, a high-level knowledge representation structure, to enhance the classification accuracy of the Content-Based Image Retrieval (CBMIR). This involves two recommended processes: categorization and retrieval. It also involves training images using a Deep Convolutional Neural Network (DCNN) during the classification stage and applying the model to CT lung images. To address hierarchical deep learning constraints, [43] has suggested a technique for fashion suggestions that utilizes backpropagation to modify various Convolutional Neural Network (CNN) branches and shared deep CNNs for relevant node attributes and classifiers. Finally, [44] has developed an ontology for rice disease, serving as a demonstration of their ontology-based plant disease and modeling technique. Their work emphasizes image-based pattern recognition combined with the use of ontology for semantic detection of plant diseases, creating new opportunities for matching disease labels to the semantics of an affected plant.

Volume: 03 / Issue: 06 / 2024 - Open Access - Website: www.mijrd.com - ISSN: 2583-0406

The research conducted by [45] introduced an ontology-driven learning technique for the classification of security requirements. This technique leverages conceptual domain knowledge and linguistic evidence. In a related work, [15] utilized natural language processing, ontology, and computer vision-based visual relationship detection to identify associations between objects in images. The significance of ontologies is evident in their critical role in clarifying relationships between terminology and conceptual equivalents, such as anatomical, part-whole, and causal relationships in the field of biomedicine, as discussed in [46].

Additionally, in [17], a methodology framework was proposed for object recognition based on ontology. This approach uses CNN features and incorporates rules based on high-level semantics. The domain ontology is employed to organize object descriptions, and an encoder model based on a multilayer technique is utilized to break down RDF-triple rules using a semantic web rule language. This novel approach integrates ontology with semantic web rule language (SWRL) rules to formally describe safety regulation knowledge, while utilizing machine vision to recognize visual data obtained from on-site pictures.

Furthermore, [47] introduced a framework for developing a symbolic model representing a scene by integrating tracking data and contextual information. The scene model, depicted using formal ontologies, facilitates reasoning procedures to derive a high-level interpretation of the scenario and provides feedback to the low-level tracking procedure, ultimately enhancing accuracy and performance. Moreover, [48] proposed a system that introduces hierarchical concepts mapping the specifics of the scene under study, along with spatial and temporal linkages, object attributes (such as shape), and visual concepts (such as color). This system integrates active contours with ontology to evaluate dynamic scenes at various granularities, yielding both semantic and numerical characterizations for each scene and its elements.

CONCLUSION

The integration of ontology with machine learning in computer vision has demonstrated significant potential in enhancing the interpretability, semantic knowledge, and performance of computer vision systems. This survey has provided a comprehensive overview of the recent advancements in ontology-integrated machine learning methods for computer vision tasks.

By examining various studies and methodologies, the survey has highlighted the effectiveness of these approaches in improving the accuracy, robustness, and explainability of computer vision models. Ontologies serve as formal representations of domain knowledge, providing structured frameworks that enhance the understanding and interpretation of visual data.

The integration of ontological knowledge with machine learning models enables the development of more accurate and reliable computer vision systems, capable of performing tasks such as object detection, image segmentation, scene understanding, and activity recognition with greater precision and efficiency. Despite the promising advancements, challenges remain in developing flexible, modular, and scalable ontology-integrated approaches that can be easily adapted to different applications. The survey emphasizes the need for further research to address these challenges and to explore new methods for integrating ontological knowledge with machine learning models in computer vision.

Volume: 03 / Issue: 06 / 2024 - Open Access - Website: www.mijrd.com - ISSN: 2583-0406

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