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Review Article

A Short Review on Supervised Machine Learning and Deep Learning Techniques in Computer Vision

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ABSTRACT

In last years, computer vision has shown important advances, mainly using the application of supervised machine learning (ML) and deep learning (DL) techniques. The objective of this review is to show a brief review of the current state of the field of supervised ML and DL techniques, especially on computer vision tasks. This study focuses on the main ideas, advantages, and applications of DL in computer vision and highlights their main concepts and advantages. This study showed the strengths, limitations, and effects of computer vision supervised ML and DL techniques.

1. BACKGROUND

Computer vision plays a pivotal role by employing image and pattern analysis methodologies to address complex challenges, treating an image as an intricate array of pixels. This field within artificial intelligence (AI) automates monitoring and inspection tasks, showcasing its capability to extract meaningful information from a diverse range of visual inputs, including digital images and videos. In essence, computer vision emerges as an indispensable component, facilitating systems in deriving valuable insights within the context of AI [1]. Computer vision goals to allow computers and machines to understand visual information, similar to humans it means the development of algorithms and techniques to analyze, process, and extract meaning from visual data [2]. Supervised ML and DL are two prominent techniques in computer vision that have developed the method visual data is analyzed and interpreted [3]. Supervised ML works in training a model developing labeled examples, utilizing algorithms such as support vector machines (SVMs), decision trees (DT), random forests (RF), and naive Bayes (NB) classifiers [4]. DL aims onartificial neural networks learned via the human brain's structure and operation. These networks, combined with many layers of connected nodes, extract representations from raw input data [5]. Figure 1 shows the classification of common ML and DL techniques. In this review of supervised ML and DL techniques in computer vision, studying their required models, architectures, strengths, and limitations.

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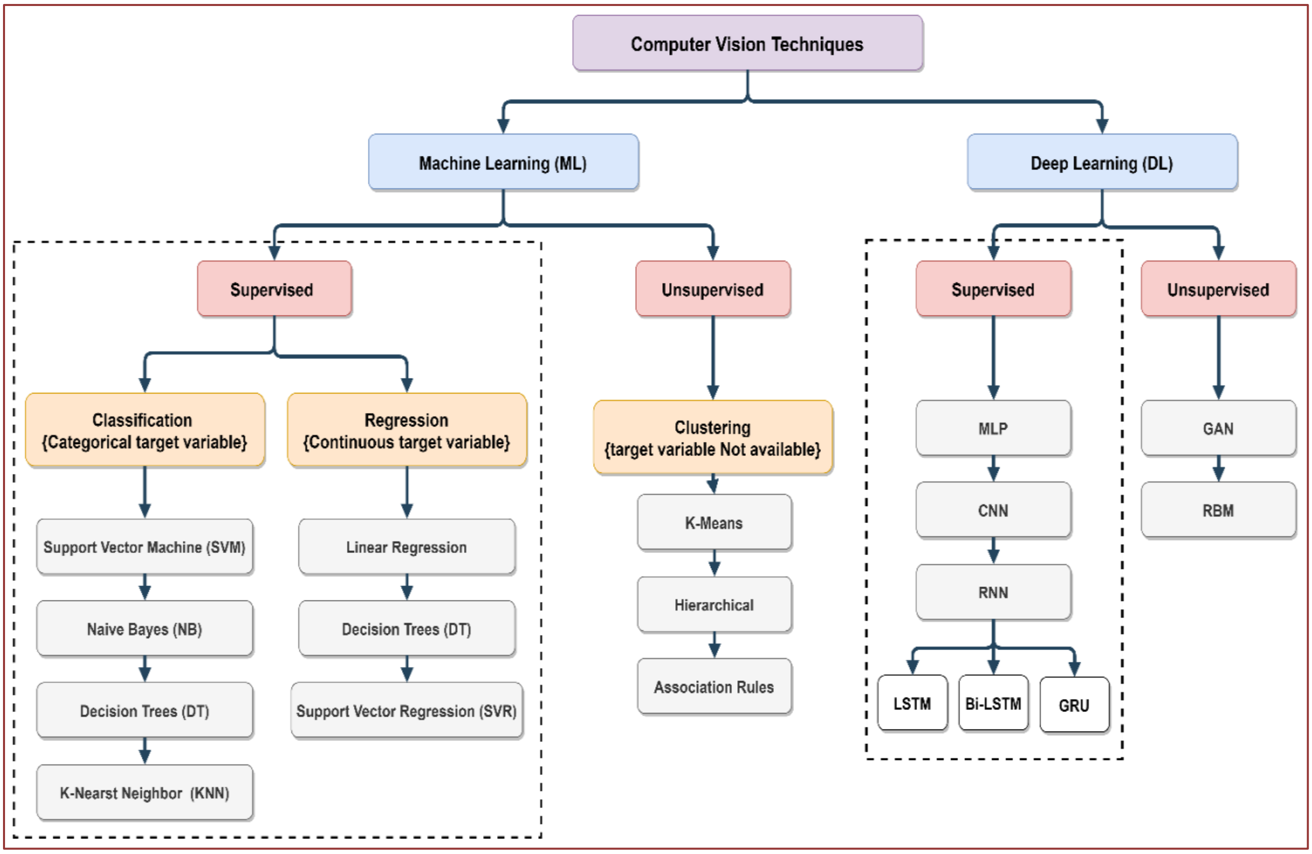

Fig. 1.Classification of common ML and DL techniques in computer vision

2. SUPERVISED MACHINE LEARNING IN COMPUTER VISION

Supervised ML is an artificial intelligence method that can train models to make predictions based on labeled input data via using optimization techniques [6]. In computer vision giving images with pre-defined comments and labels. Traditional ML algorithms such as SVM and RF are used for computer vision tasks [7]. These algorithms mostly depend on the properties extracted from images. These features are utilized to train models based on learning patterns and make predictions [8]. Common tasks within computer vision for supervised learning algorithms are object detection and classification. Object detection involves the use of supervised learning algorithms to acquire the capability of identifying and localizing objects within images. Image classification utilizes supervised learning algorithms to acquire the ability to assign a class label (e.g., "person," "dog", "car") to an image [9].

2.1 Popular Supervised ML algorithms

- Support Vector Machines are used for image classification tasks, learning to classify images into predefined classifications. SVM draws input images to a high-dimensional feature space and finds an optimal hyperplane to separate several classes [10][11].
- Random Forests are utilized for object detection, where they utilize an ensemble of decision trees [12]. Each decision tree alone predicts the presence of an object within an image, and the final result is achieved through a voting or averaging mechanism [13].
- Naive Bayes are frequently utilized for tasks like document classification and face recognition [14]. These algorithms consider individuality among features, making them computationally efficient and right for large-scale applications [15].

2.2 Strengths and limitations

As shown in table 1 the strengths and limitations of Supervised ML techniques in computer vision [16][17].

TABLE I. THE STRENGTHS AND LIMITATIONS OF SUPERVISED ML TECHNIQUES IN COMPUTER VISION

Strengths	**Limitations**
Ability to manage complex decision limitations and high-dimensional feature spaces.	Requirement on handcrafted features, which may require field expertise and manual feature engineering.
Well-established algorithms with interpretable results.	Sensitivity to outliers and noise in the training data.
Effective use of labeled training data for training models.	Support on labeled training data, which can be expensive and time-consuming to obtain.
	Difficulty in running large-scale datasets due to computational limitations.

2.3 Performance comparison

The performance of various supervised ML algorithms is different dependent on the specific computer vision task [18]. Several studies have described relative evaluations of algorithms like SVM, RF, and NB in image classification, object detection, and image segmentation [19]. The performance metrics such as accuracy, precision, recall, and F1 score are commonly utilized to compare the algorithms' efficiency in different tasks [20].

2.4 Gaps and areas for improvement

The success of supervised ML techniques in computer vision, there are still areas for improvement [21],[22]. Some gaps contain:

- Limited generalization capability to control complex and separate real-world scenarios.
- Challenges in processing large-scale datasets and real-time management requirements.
- Difficulty in getting spatial dependencies and contextual information in images.
- Discovery of techniques to decrease handcrafted features and improve feature extraction skills.

3. DEEP LEARNING TECHNIQUES IN COMPUTER VISION

DL is a subset of ML and has succeeded in importance in computer vision due to its ability to automatically learn classified descriptions from raw data [23]. CNN is the core of DL model in computer vision. CNNs contain multiple layers of connected neurons, motivated via the organization of the visual cortex in humans [24]. CNNs can learn to extract important features from pixels, reduction the need for manual feature engineering. This allows them to capture complex patterns and structures in images, important to better performance in different computer vision tasks [25].
DL techniques have utilized computer vision research, running to significant findings and results. Studies utilizing DL methodologies such as CNN, RNNs, and their options (ResNet, Inception, LSTM) to address many computer vision tasks [26][27][28][29]. These techniques weigh deep neural networks with multiple layers to automatically learn classified features and statements from data [30]. Researchers have stated significant achievements utilizing DL in computer vision [31][32]. For example, CNNs have shown special performance in image classification tasks, outperforming utilizing ML algorithms. RNNs, with their ability to capture temporal dependencies, have been successful in tasks like video analysis and sequence generation [33][34].

3.1 Popular deep learning architectures and applications

- CNNs have been usually utilized for image-related tasks, such as image classification, object detection, and semantic segmentation [35]. They contain convolutional layers, pooling layers, and fully connected layers, enabling the network to learn spatial hierarchies of features [36].
- RNNs are well-suited for tasks relating to subsequent data, such as video analysis, caption generation, and speech recognition [37]. They utilize continuing relations to capture temporal dependencies and have been extended with

options like Long Short-Term Memory (LSTM) and Gated Recurrent Units (GRU) to address the vanishing gradient problem [38][39].

- Variants of CNNs and RNNs: Architectures like ResNet, Inception, and DenseNet have been developed to address the challenges of training deep neural networks [40]. These architectures present skip connections, parallel branches, and dense connections, respectively, to improve gradient flow, model efficiency, and feature reuse [41].

3.2 Performance comparison and strengths and limitations

There are different DL architectures that show varying performance in computer vision tasks [42]. Performance is evaluated utilizing metrics such as accuracy, precision, recall, and F1 score [43][44]. Each architecture has its strengths and limitations:

- CNNs have bested in image classification and object detection, thanks to their ability to capture spatial hierarchies of features [45]. However, they may work with capturing long-range needs in sequential data [46].
- RNNs are effective in tasks relating to sequential data, but they may be challenged in processing long sequences due to vanishing and exploding gradients [47].
- The other architectures like ResNet, Inception, and DenseNet have improved the training of deep networks, but they may be computationally costly and require larger amounts of training data [48].

3.3 Advancements in pre-training, transfer learning, and data augmentation

There are a lot of studies have made significant developments in improving DL models' performance in computer vision through the following techniques [49], [50]:

- Pre-training on large-scale datasets, such as ImageNet, supported by fine-tuning on the target task, improves the initialisation of the networks with significant descriptions and boosts performance [51].
- Transfer learning allows pre-trained models on one task and transferring their learned representations to related tasks with limited labeled data, improving generalization and reducing training time [52].
- Data augmentation Techniques such as rotation, translation, scaling, and adding noise to training data enhance the dataset, enabling the model to learn from diverse variations and improve robustness [53].

4. HYBRID APPROACHES AND INTEGRATION OF SUPERVISED MACHINE LEARNING WITH DEEP LEARNING

4.1 Studies combining supervised machine learning and deep learning:

Many studies have explored the use of supervised machine learning and deep learning techniques in computer vision [54]. These hybrid methods aim to enhance performance and address the limitations of individual methods like combination DL models with usual classifiers, utilized DL for feature extraction followed by supervised ML for classification, and combining supervised learning into deep architecture [55][56].

4.2 Methodologies for leveraging the strengths of both approaches

The hybrid methods utilize DL for feature extraction because of the ability to automatically learn hierarchical representations from raw data [57]. The extracted features are utilized as inputs to supervise ML algorithms for classification or regression tasks this allows the DL model to capture complex patterns and representations, but the supervised learning factor supports interpretability and strength [58].

The combination of supervised learning into deep architectures, such as attention mechanisms or reinforcement learning to control the learning process [59]. This can develop the discriminatory power of deep models and enhance their generalization capacities via supporting labeled data [60].

4.3 Hybrid supervised machine learning and deep learning (Benefits and challenges)

As shown in table 2 the benefits and challenges of hybrid-supervised ML and DL techniques in computer vision [3][61].

TABLE II. THE BENEFITS AND CHALLENGES OF HYBRID SSUPERVISED ML AND DL IN COMPUTER VISION

Benefits	**Challenges**
Improved performance	Complexity
Feature learning and interpretability	Computational requirements
Transferability	Data requirements

4.4 Performance comparison with standalone techniques

The performance of hybrid methods combining supervised ML and DL can vary dependent on the specific task and dataset. The hybrid models have improved performance compared to individual supervised ML or DL models [62]. The efficiency of these methods depends on factors such as the quality and size of the labeled dataset, the complexity of the task, and the right combination of the two techniques.

5. DISCUSSION, GAPS AND ISSUES

There are a lot of gaps and limitations in recent research on supervised ML and DL models in computer vision. These include their generalization of various data, interpretation and explanation, and data efficiency. DL models are measured black boxes due to their complex nature, which limits their implementation in essential fields. Data efficiency is also a challenge, as they require large amounts of labeled data for training, which can be expensive and time-consuming. The unresolved challenges contain real-time processing, transfer learning across areas, and continual learning and flexibility. While DL models have achieved good results, their computational requirements can be prohibitive for real-time applications. Transfer learning has shown potential in pre-trained models, but challenges stay in efficiently transferring learned representations across several fields. Potential directions for future research include improving interpretability, strength and adversarial defence, data-efficient learning, domain modification and transfer learning, and ethical points and fairness. In the future the researchers can advance the field of supervised ML and DL in computer vision, making it stronger, interpretable, and ethical while improving generalization abilities and real-world applicability.

6. CONCLUSION

The supervised ML and DL techniques in computer vision have shown good results in increasing performance and addressing limitations. However, challenges such as computational difficulty, large, labeled datasets, and interpretability of DL models need further research. However, these findings have important effects for practical applications in computer vision, such as object recognition, image classification, and semantic segmentation. The interpretability presented by supervised learning is particularly valuable in domains like healthcare and autonomous systems. In the future should focus on developing efficient hybrid model architectures, improving interpretability techniques, exploring data-efficient learning methods, improving robustness beside adversarial attacks, and addressing ethical considerations in computer vision algorithms.

Conflict Of Interest

The author's paper declares that there are no relationships or affiliations that could create conflicts of interest.

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