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# DEEP LEARNING AND PHOTOGRAMMETRY: A REVIEW OF CURRENT ADVANCES AND FUTURE DIRECTIONS

## *APRENDIZAJE PROFUNDO Y FOTOGRAMETRÍA: UNA REVISIÓN DE LOS AVANCES ACTUALES Y FUTURAS DIRECCIONES*

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**Abstract:**

This article provides a comprehensive review of current deep learning techniques applied to photogrammetry. It examines recent progress and the transformation of photogrammetric workflows through the integration of (CNNs) and (GANs). Applications such as 3D reconstruction, image enhancement, semantic segmentation and change detection are explored. The review identifies key limitations and challenges while outlining future directions for this rapidly evolving field. As technologies mature, deep learning is expected to play a pivotal role in optimizing photogrammetric products for sectors including agriculture, environmental monitoring and infrastructure management.

**Key words:** Deep learning, Photogrammetry, 3D reconstruction, Semantic segmentation, Change detection

**Resumen:**

Este artículo proporciona una revisión exhaustiva del estado actual de las técnicas de aprendizaje profundo en el campo de la fotogrametría. Examina la transformación, el progreso reciente y los avances en fotogrametría, mejorando la precisión, automatización y capacidad de análisis de datos geoespaciales. Se revisan los avances más recientes en la integración de arquitecturas como las redes neuronales convolucionales (CNNs) y las redes generativas antagónicas (GANs) en diversas aplicaciones fotogramétricas, tales como la reconstrucción 3D, la superresolución y mejora de imágenes, la segmentación semántica, y la detección de cambios. La revisión abarca la investigación y los desarrollos hasta el año 2024, con un enfoque en las publicaciones en revistas y artículos científicos. El artículo tiene como objetivo identificar las limitaciones, los desafíos clave y las direcciones futuras en la aplicación del aprendizaje profundo a la fotogrametría, con el objetivo de guiar la investigación en este campo en rápida evolución. A medida que estas tecnologías continúan avanzando, se espera que el deep learning desempeñe un papel fundamental en la optimización y expansión de las aplicaciones de la fotogrametría en sectores como la agricultura, el monitoreo ambiental y la gestión de infraestructuras.

**Palabras clave:** Aprendizaje profundo, Fotogrametría, Reconstrucción 3D, Segmentación semántica, Detección de cambios

## 1. Introduction

Photogrammetry has been fundamental in the field of geomatics and disciplines such as geographic information systems, sensors and cartography, among others, for over a century. It has enabled us to make precise measurements and create representations of the real world through the use of photographic images. With the advancement and use of technology and new manned and unmanned aerial platforms, photogrammetry has evolved considerably, reaching the point of supporting and revolutionizing fields such as agriculture, urban planning and the environment, among many others. However, traditional methods used in photogrammetry, such as geometric correlation and manual image analysis, can present limitations, especially when dealing with complex scenarios such as low resolution, variable lighting, the need for accurate object identification and occlusions.

The development of deep learning, a subdiscipline of machine learning, has driven a new technological revolution that has catapulted the analytical and

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processing capabilities of photogrammetric images. Photogrammetry has leveraged the application of these modern architectures—such as Convolutional Neural Networks (CNNs) and Generative Adversarial Networks (GANs)—to improve the precision and automation of its results and products, allowing challenges that once seemed insurmountable to be addressed more easily today.

This article provides a comprehensive review of recent advances in the use of deep learning in photogrammetry, highlighting its applications in 3D (Ponti and da Costa 2018; Gaetano *et al.* 2018), image enhancement (Xu *et al.* 2017; de Jong *et al.* 2020), and change detection (Khelifi and Mignotte 2020; Cheng *et al.* 2024), as well as the challenges that still need to be overcome to maximize its potential across various industries.

## 2. Applications of Deep Learning in Photogrammetry

Deep learning has emerged as a transformative approach in the field of photogrammetry, revolutionizing traditional techniques and paving the way for unprecedented advances. These improvements have enabled photogrammetry and deep learning to jointly address highly complex challenges (Lunga *et al.* 2019; Persello *et al.* 2021), such as 3D reconstruction, image segmentation and temporal image analysis, significantly increasing the efficiency and accuracy of numerous key processes. As deep learning models are integrated into photogrammetric workflows, new opportunities arise to improve the quality and speed of results and to tackle problems previously difficult to solve with conventional techniques (Deng 2016; Lunga *et al.* 2021; Ponti and da Costa 2018).

This section reviews some of the main applications of deep learning in photogrammetry, categorizing different approaches and highlighting their benefits and impacts on this discipline. The thematic classification used here is based on several fundamental pillars of photogrammetry.

### 2.1. 3D Reconstruction

Three-dimensional reconstruction from images is one of the main strengths and challenges of photogrammetry. This process has been used in multiple tasks such as 3D modeling, mapping, infrastructure and cultural heritage analysis and urban planning. The integration of 3D reconstruction with deep learning techniques (Lunga *et al.* 2021; Ongie *et al.* 2020; Ponti and da Costa 2018) has enabled significant advancements by simplifying, automating and improving the accuracy of these processes. This allows the generation of more precise, detailed and realistically textured 3D models from 2D image sets (Albuquerque 2022; Gaetano *et al.* 2018; Lunga *et al*. 2021; Trujillo-Jiménez 2024).

Photogrammetry has traditionally relied on geometric methods and feature-matching algorithms such as Scale-Invariant Feature Transform (SIFT) or Speeded-Up Robust Features (SURF). However, these techniques face limitations when dealing with complex scenes with low texture, occlusions or insufficient resolution. In such scenarios, deep learning models, particularly CNNs, have shown superior results by learning robust representations of visual features and spatial relationships, allowing more accurate 3D geometry reconstruction from 2D data (Zhong *et al.* 2024).

CNNs have proven particularly effective in this domain, as they can learn relevant feature hierarchies from complex input data, enabling more precise and detailed reconstructions (Ongie *et al.* 2020). They are especially effective in automating and improving the reconstruction process through the extraction, identification and correlation of key features in image sets (Ponti and da Costa 2018). significantly improving reconstruction quality compared to traditional methods based on bundle adjustment and triangulation (Gaetano *et al.* 2018). Furthermore, it has been observed that integrating deep learning techniques with photogrammetry not only improves the accuracy of the 3D models generated but also significantly reduces the processing time required to obtain results (Gaetano *et al.* 2018; Valerga-Puerta *et al.* 2020). Several studies have demonstrated that deep CNN are capable of predicting depth maps and 3D geometry from a single 2D image (Ongie *et al*. 2020; Ponti and da Costa 2018; Zhong *et al.* 2024).

Other deep learning approaches, such as Generative Adversarial Networks (GANs), have also shown promising capabilities for realistic synthesis of 3D geometries and textures. GANs have been used, for example, to fill gaps and extrapolate 3D geometry from incomplete or partial data (Laina *et al.* 2016; Zhao *et al.* 2018) and have been particularly effective in correcting artifacts and generating fine-level details (Albuquerque 2022; Lattas *et al.* 2020).

The 3D reconstruction of irregular timber structures in the construction field has been successfully addressed through the use of close-range digital photogrammetry and deep learning techniques (Arias *et al.* 2007). The 3D reconstruction of archaeological objects and cultural heritage has also received special attention, where deep learning models have proven to be more effective than traditional approaches in scenarios with occlusions, low texture and limited input image resolution. 3D reconstruction from RGB-D images has benefited from deep learning advances, which have shown greater robustness and accuracy than traditional methods, especially in environments with challenging lighting and occlusions (Qin and Gruen 2021; Trujillo-Jiménez 2024).

Hybrid approaches that combine the strengths of traditional photogrammetry, the capabilities of deep learning models and multisensor data have improved the quality of generated 3D models by leveraging the complementary advantages of each approach (Albuquerque 2022; Zhong *et al.* 2021, 2024). One example of this approach is the use of CNNs together with LiDAR point cloud data to generate more accurate and complete 3D reconstructions of urban environments (Chen *et al.* 2020b).

The full automation of the 3D reconstruction process is another key benefit of deep learning, eliminating the need for the intensive manual intervention required by traditional photogrammetric methods. In this way, human supervision of processes such as image alignment and dense point cloud generation is significantly reduced. This brings important benefits in terms of reducing human errors, processing times and associated costs. These advantages are particularly important in the development or application of these techniques for emergency response situations such as natural disasters, where response time becomes a key or even decisive factor (Trujillo-Jiménez 2024).

### 2.2. Semantic Segmentation and Classification

Beyond geometric reconstruction, the integration of deep learning techniques in photogrammetry has led to significant advancements in the field of semantic segmentation and classification of elements and objects in 3D point clouds. The identification and classification of features such as water bodies, vegetation and buildings are fundamental processes in photogrammetry. This combination has revolutionized such procedures, increasing the capacity of systems to segment complex image sets with high levels of detail and precision (Beckman *et al.* 2019; Gray *et al.* 2019).

Segmentation and classification in photogrammetric processes have traditionally relied on mathematical and geometric algorithms, in addition to manual supervision and editing, which obviously involves considerable human effort and is highly prone to error—especially in scenarios where the images are of low quality or exhibit high spatial variability. These automated deep learning-based processes for semantic segmentation and classification facilitate the extraction and structuring of high-quality geospatial information from photographic data, which is essential for the development of multiple applications such as thematic mapping, land use analysis and infrastructure management (Caicedo *et al.* 2022). Scientific literature shows that deep learning models far outperform traditional segmentation and classification methods, particularly in complex scenarios with high variability and heterogeneity of the objects to be classified.

The ability of CNNs to learn high-level representations from complex visual data enables them to accurately identify and classify specific elements in both 2D and 3D models. CNNs can be trained to identify and classify different types of objects in images with remarkable precision using labeled datasets. Recent studies have shown that CNNs can learn to segment and classify natural and artificial elements—such as urban zones, forested areas, crops, or water bodies—from aerial and satellite imagery with high detail, even under highly variable lighting and resolution condition (Eldefrawy *et al.* 2022; Grilli *et al.* 2021).

The classification of different crop types and the monitoring of their health and productivity from drone-captured imagery using CNNs has also been successfully addressed. This allows farmers and land managers to obtain detailed and relevant information about the state of their crops, facilitating decision-making, reducing costs and optimizing tasks such as fertilizer application and pest control (Gené-Mola *et al.* 2020).

Similarly, the use of advanced semantic segmentation techniques such as Mask R-CNN has enabled the accurate identification and extraction of specific elements in 3D point clouds, including vehicles, buildings and road signage, with applications in fields such as urban planning, cadastral mapping and traffic management (Ahmed *et al.* 2021). Deep learning-based semantic segmentation in urban contexts facilitates the extraction, identification, classification and monitoring of roads, bridges, buildings and various infrastructures—proving highly valuable for improving urban mapping processes, city maintenance, emergency management and smart city systems (He *et al.* 2023; Lee *et al.* 2019; Minaee *et al.* 2022). These deep learning approaches have also proven effective for semantic classification of elements in cultural heritage scenes and archaeological sites. Deep learning models can learn hierarchical features at a high level, including shape, texture and relative position of objects, which gives them strong discriminatory and classification power—allowing them to differentiate materials and detect anomalies with great efficiency and accuracy (Morelli *et al.* 2022).

### 2.3. Super-Resolution and Image Enhancement

One of the most promising areas of deep learning in photogrammetry is the improvement of image quality and resolution used in photogrammetric processes. Many applications require high-resolution, high-quality images. However, this is not always possible due to limitations in capture systems, environmental conditions, or even financial constraints. This is where deep learning techniques have proven to be highly effective in enhancing resolution, sharpness and overall image quality, as well as in reducing noise and artifacts, through what is known as super-resolution.

Traditional methods for improving image resolution are usually based on interpolation or frequency techniques, such as bicubic interpolation or Fourier-based super-resolution approaches. However, these methods have significant limitations in their ability to recover fine details and deal with complex variations present in the images (Beckman *et al.* 2019). In contrast, deep learning approaches—particularly through the use of GANs and CNNs have facilitated the development of more advanced methods capable of learning directly from data, thereby overcoming the constraints of traditional techniques (de Jong *et al.* 2020).

These deep learning models are trained on pairs of low- and high-resolution images, allowing them to learn the features and transformations necessary to enhance the input image quality and generate higher-resolution versions with increased sharpness and reduced noise. In the context of photogrammetry, the application of these super-resolution methods offers important benefits, such as the ability to work with lower-resolution images without sacrificing final output quality, or improving the information extracted from degraded or low signal-to-noise ratio images (Xu *et al.* 2017; Yaqub *et al.* 2022).

Additionally, deep learning-based approaches for image enhancement have also proven effective in correcting distortions, increasing contrast and improving other important aspects of image quality, such as edge clarity and artifact reduction. These capabilities represent a major advantage in photogrammetric applications where image quality is fundamental (Tu *et al*. 2023; Upadhyay and Awate 2019).

One of the most interesting advances in this field is the use of GANs for improving image resolution and quality.

GANs work by pitting two neural networks against each other: a generator and a discriminator. The generator is trained to produce high-resolution images from low-resolution input, while the discriminator is trained to distinguish between the generated images and real high-resolution ones (de Jong *et al*. 2020). GANs have also demonstrated high efficiency in recovering fine details and enhancing the resolution of satellite and aerial images, enabling better identification and analysis of spatial features (Beckman *et al.* 2019).

On the other hand, CNNs have proven highly effective at learning complex noise patterns in images (Xu *et al.* 2017) and eliminating them efficiently. This makes them a valuable tool for quality enhancement and noise mitigation in images used in photogrammetric processes (Braun and Borrmann 2019; Chen *et al.* 2020c; Pandey *et al.* 2018). This capability, combined with their ability to solve super-resolution problems, has made CNNs essential when working with images captured under adverse conditions, such as low lighting or poor atmospheric conditions.

Another interesting development in this field is the combination of GANs and CNNs to achieve comprehensive image quality enhancement, leveraging the strengths of both approaches to achieve superior results compared to using either technique alone. This deep learning strategy has been effectively used to enhance the quality and resolution of images captured by drones—a critical capability for the accurate detection and classification of landscape features, such as agricultural crops and urban infrastructure, in remote sensing and monitoring applications (Ko *et al.* 2021).

## 2.4. Temporal Analysis and Change Detection

Another area where deep learning has demonstrated great potential in photogrammetry is in temporal analysis and change detection across different periods or moments in time. Traditionally, change detection between multitemporal images has relied on techniques such as image differencing, post-classification comparison, or change vector analysis. However, these approaches present limitations in terms of accuracy, the ability to detect complex changes and robustness against variations in image acquisition conditions (Cheng *et al*. 2024; Pun *et al.* 2023; Santos Silva *et al.* 2022). Some notable studies in this context include (Cheng *et al*. 2024; Khelifi and Mignotte 2020; Mou *et al*. 2019), which present significant advancements in the field of change detection through deep learning, identifying new promising directions for future development (Cheng *et al.* 2024; Khelifi and Mignotte 2020).

Deep learning methods have proven to be a highly promising alternative to address these limitations. Specifically, CNNs have emerged as powerful tools for the automatic extraction of relevant features from images, enabling more precise and robust change detection in the face of factors such as lighting variation, viewing angles, or atmospheric conditions (Khelifi and Mignotte 2020). The application of deep learning techniques like Recurrent Neural Networks (RNNs) and their variants such as long short-term memory (LSTM) networks to the analysis of temporal image sequences has proven effective for detecting and mapping complex territorial changes over time, such as urban growth, deforestation, floods and more (Khelifi and Mignotte 2020).

LSTM networks in particular have demonstrated high effectiveness in detecting changes in urban areas, where object variability and the density introduced by urban infrastructure make traditional methods less effective (Khelifi and Mignotte 2020), This RNN variant can retain relevant information over longer periods, better capturing gradual changes or those dependent on past events (Flórez-Pareja *et al.* 2023). In various studies, these networks have successfully monitored urban expansion and growth more efficiently, contributing to higher quality responses for decision-making processes (Santos 2019).

In the context of disaster management, rapid and accurate change detection is critically important. Deep learning techniques such as CNNs and RNNs have proven effective for analyzing satellite and aerial imagery in near real-time, enabling swift and effective emergency response. In crisis situations—such as following an earthquake or hurricane—the processing of drone-captured images using deep learning techniques enables quick identification of affected areas, assessment of damage severity and prioritization of rescue and response actions (Eltner *et al.* 2021). This approach allows for image analysis that is much faster and more accurate than traditional methods, reducing the human errors typically associated with those techniques.

## 2.5. Applications in Agriculture and the Environment

Deep learning has had a major impact and has revolutionized photogrammetry in the fields of agriculture and environmental management. Deep learning techniques have proven to be highly effective for classifying and segmenting crops and vegetation types from aerial and satellite imagery. CNNs have achieved great precision in identifying different crop types, plant diseases, weeds and even the maturity state of crops (Ahmed *et al.* 2023). Some works in this area have successfully detected crop variations caused by water stress, nutrient deficiencies and disease presence—before these symptoms become visible to the naked eye (Beckman *et al.* 2019; Chen *et al.* 2020c; Gené-Mola *et al. 2020*).

In this context, CNNs have shown great ability to extract relevant image features such as texture, color and structure, allowing for accurate classification of various types of land cover and vegetation (Ahmed *et al.* 2021; Li *et al.* 2023; Muthukumarana and Aponso 2020; Yaqub *et al.* 2022).

These capabilities are highly valuable for more efficient agricultural resource management and cultivation practice planning (Ahmed *et al.* 2021; Nex *et al.* 2019). Neural networks have proven to be more accurate at segmenting active crop zones from uncultivated areas. This capacity can be especially helpful in fields such as precision agriculture, where optimizing resources like water, fertilizers and pesticides is key to improving yield and productivity (Gray *et al.* 2019).

 

Likewise, deep learning has been successfully used for mapping and monitoring ecosystems and natural resources—such as forests, wetland and coastal areas—using satellite and aerial imagery. These applications include detecting changes in vegetation cover, assessing biodiversity, monitoring protected areas, habitat mapping and evaluating ecosystem health. The combination of aerial and satellite imagery with data from remote sensors enables CNNs to generate detailed maps of vegetation coverage, biodiversity and environmental changes (*e.g.,* illegal deforestation, urban expansion, or climate change effects on natural ecosystems). This is fundamental for the sustainable management of natural resources (Ahmed *et al.* 2021; Ahmed *et al.* 2023; Eltner *et al.* 2021; Li *et al.* 2023; Muthukumarana and Aponso 2020).

The application of deep learning methods has also proven valuable for detecting and identifying pests and diseases that affect forests and agricultural crops. CNNs can be trained to recognize distinctive visual patterns indicative of pest infestations or disease outbreaks in aerial images. This allows for timely identification and facilitates a rapid intervention by farmers. This kind of early monitoring capability is fundamental for effective natural resource management and environmental conservation efforts (Santos 2019).

### 2.6. Infrastructure Inspection and Monitoring

Traditionally, the analysis of structural characteristics and the condition of infrastructure—such as bridges, buildings, pipelines, etc.—has been conducted manually, which also requires significant effort and time from experts, especially in areas that are difficult to access or present high safety risks. Deep learning techniques applied to images captured by drones and other remote sensing systems have revolutionized this field, enabling more efficient inspection and monitoring by processing captured images in an automatic or semi-automatic manner. This allows for the identification of damage, defects, deterioration, pathologies, structural issues, cracks, corrosion and other infrastructure problems much more effectively than traditional methods (Carrasco *et al.* 2022).

The use of neural networks in this area has shown great potential for identifying and classifying different structural elements in images —such as beams, columns and supports— and thereby assessing their condition in real time. This capability can be crucial for early detection of issues, preventing them from developing into serious failures that could compromise the safety of infrastructure and the people who use it (Figueroa-Yaguana 2022).

In this field, CNNs have been trained to automatically detect structural elements in bridges (Herraiz *et al.* 2019; Moura *et al.* 2021; Wuttke *et al.* 2021) using aerial imagery and to perform detailed assessments of their conservation status by identifying problems such as cracks, corrosion and displacements (Trujillo-Jiménez 2024).

### 2.7. Integration of Technologies and Sensors

The integration of technologies such as remote sensors, robotics, unmanned aerial vehicles (UAVs) and geographic information systems (GIS) with data from various types of sensors —such as LiDAR, multispectral, thermal and hyperspectral cameras— alongside deep learning techniques, has enabled the development of more comprehensive and accurate solutions for applications across multiple fields.

The fusion of different data sources, including LiDAR point clouds, aerial and terrestrial photographs, thermography and multispectral images, allows for the generation of high-resolution 3D models, vegetation maps, change detection and detailed assessments of infrastructure conditions. These outputs are fundamental for planning, maintenance and management processes (Zhong *et al.* 2024).

The integration of multispectral and hyperspectral cameras on aerial and satellite platforms has significantly improved the ability to monitor vegetation health and detect changes in land use, due to their capacity to capture information across multiple bands of the electromagnetic spectrum. This facilitates more accurate discrimination between vegetation types and early identification of water stress or pest outbreaks. When combined with deep learning techniques, it is possible to develop models that not only classify vegetation but also predict its health status and productivity (Alvarenga-Souto 2019; Ferreira-Sales 2023). Similarly, thermal sensors have expanded photogrammetry applications in infrastructure management and environmental conservation by detecting temperature variations that indicate anomalies such as water leaks, heat losses, or forest fires. By combining thermal images with other data and processing them using deep learning, models can improve the precision of structural or environmental problem detection (Buyukdemircioglu *et al.* 2022). Additionally, the use of drones and satellites equipped with multiple sensors to capture data from different angles allows for the creation of real-time maps and 3D models, enhancing the precision of infrastructure monitoring, urban planning and resource management and facilitating faster response to disasters or land use changes (Gruen 2021).

## 3. Challenges and Limitations

While the progress of deep learning in photogrammetry has been remarkable, several challenges and limitations remain that deserve deeper exploration. Analyzing these limitations is ultimately essential to maximize the potential of this technology within the field of photogrammetry.

One key challenge is the need for robust and interpretable deep learning models that can provide insights into their decision-making processes, rather than functioning as “black boxes” (Zhu *et al.* 2017), This lack of transparency means it is difficult to understand how or why a model makes certain decisions. This is particularly important in applications where clarity and explain ability are critical, such as monitoring critical infrastructure or urban planning (Remondino 2019). Without a clear understanding of a model's outputs, engineers and decision-makers may be hesitant to rely on such technologies for critical operations. In addition, the reproducibility of results and comparison between different deep learning approaches remain important challenges due to the complexity of the models and their sensitivity to hyper parameters.

A major limitation of neural networks is their reliance on large training datasets, which can restrict their applicability in resource-constrained environments or scenarios with limited data. CNNs and GANs, in particular, require extensive and well-labeled datasets to learn complex and generalized patterns that can be transferred to new cases. The issue lies in collecting high-quality data, which often demands significant resource investment in terms of time and cost (Beckman *et al.* 2019; Ko *et al.* 2021). Another challenge is adapting deep learning approaches to contexts with limited resources and data availability, such as in developing countries or remote regions. Developing efficient, low-data deep learning techniques that can function in such conditions, is essential to broaden the global reach and applicability of these technologies (Beckman *et al.* 2019; Ko *et al.* 2021).

Significant data variation—in resolution, lighting, angle and quality—also presents a major difficulty in the photogrammetric context. Ensuring that deep learning models remain robust under these conditions is crucial to ensure their reliability in real-world applications. In environmental monitoring, for instance, where lighting and weather conditions can vary drastically, models must maintain stable performance. This requires constant adjustments and recalibration to maintain adequate system reliability (Buyukdemircioglu *et al.* 2022). The need for continuous data normalization and the lack of standardized data input formats also remains significant barriers to broader adoption of deep learning in this domain (Alvarenga-Souto, 2019).

The high computational cost and energy consumption required to train and run high-performance deep learning models also present a challenge for implementation in low-resource devices, such as edge sensors and embedded systems used in photogrammetric applications. While advances in hardware and algorithms have helped mitigate this issue, further research into model optimization and compression techniques is necessary to enable deployment in constrained environments. This challenge becomes especially significant when real-time processing is required, such as in mobile applications, IoT, or disaster response and critical infrastructure inspection scenarios where rapid response times are crucial (Chen *et al.* 2020a; Eltner *et al.* 2021).

Another key challenge for the widespread adoption of deep learning in photogrammetry is the development of frameworks that facilitate the integration and combination of deep learning with traditional image processing and spatial analysis techniques. These complementary approaches should be explored thoroughly to leverage the best of both worlds and produce more robust and versatile solutions.

Developing deep learning models that can operate effectively across diverse geographical and regional contexts represents another significant challenge. Given the variability in environmental, cultural and geographic conditions worldwide, it is crucial for these models to generalize beyond their initial training datasets. A lack of robustness and generalizability may limit the practical usefulness of deep learning in photogrammetry, requiring retraining or fine-tuning that increases costs and implementation time (Pasanau-Aguado 2024; Santos 2019).

An additional important challenge is ensuring integration and interoperability between deep learning systems and existing photogrammetric platforms and architectures. This demands a holistic and systemic approach. Moreover, integrating various types of sensors and technologies into a unified deep learning framework adds another layer of complexity. The variability in data captured from sensors like LiDAR, multispectral, thermal cameras and also from platforms such as UAVs, introduces additional challenges in terms of data fusion and processing. For models to be more effective, they must be able to handle and process heterogeneous data in a coherent and precise way, which requires advanced data fusion algorithms and robust models that can adapt to differences in data quality and format (Ferreira-Sales 2023; Gruen 2021).

Finally, another area of concern is the development of deep learning techniques capable of effectively handling the diverse and complex nature of photogrammetric data, including multimodal and multitemporal datasets. Advances in this direction will be crucial to unlocking the full potential of deep learning in photogrammetry, allowing for a more comprehensive and holistic analysis of the built environment and natural landscapes.

## 4. Future Perspectives

The outlook for incorporating deep learning into photogrammetry appears highly promising. As novel and improved algorithms emerge, alongside advanced data processing techniques, the opportunities to integrate deep learning into this field are unlimited and multifaceted.

One of the main areas of future focus will be expanding the applicability of deep learning beyond scenarios with large datasets and unlimited computational resources. The ability to develop deep learning models that can operate effectively with smaller datasets and limited computational power is crucial to democratizing the use of these techniques across a broader range of photogrammetric applications, particularly in resource-constrained environments (Jithendra and Mittal 2021). As deep learning becomes increasingly user-friendly and accessible —facilitated by the availability of open-source tools and the expansion of data resources— we can anticipate broader adoption of these technologies among professionals and organizations in their day-to-day operations, from small mapping companies to large government and non-profit entities responsible for managing vast regions and natural resources (Figueroa-Yaguana 2022; Trujillo-Jiménez 2024).

Likewise, the development of more interpretable and explainable deep learning approaches is expected to become a growing area of interest in the coming years. This will help improve the trustworthiness and adoption of these models in critical applications where appropriate explanation of the decision-making process is required (Jithendra and Mittal 2021).

 

Another important direction will be the exploration of deep learning techniques capable of effectively handling multi-source and multitemporal photogrammetric data. This will enable more comprehensive and holistic analyses of evolving environments. Integrating data from various types of sensors has the potential to improve the accuracy and fidelity of 3D models, which in turn can unlock a wide range of novel applications in domains such as precision agriculture, natural resource management and urban planning. (Ferreira-Sales 2023; Gruen 2021).

The combined use of deep learning with traditional photogrammetric and image processing techniques is also expected to give rise to more robust and versatile hybrid solutions that leverage the strengths of both approaches. Integrating deep learning with traditional photogrammetric techniques —such as Structure-from-Motion and Bundle Adjustment— presents an exciting opportunity for hybrid methodologies that capitalize on the complementary capabilities of these two paradigms. By combining the powerful feature extraction and classification capabilities of deep learning with the geometric and spatial modeling strengths of traditional photogrammetry, researchers and professionals can develop innovative solutions that are more adaptable, accurate and reliable across a wide range of photogrammetric applications and environmental conditions. Hybrid approaches that seamlessly integrate the best of both worlds have the potential to push the boundaries of what is possible in photogrammetry, unlocking new opportunities in 3D reconstruction, mapping, monitoring and analysis of the physical world.

Finally, integrating deep learning with other advanced approaches —such as computer vision, artificial intelligence and robotics— opens exciting possibilities for the future of photogrammetry. Efforts to combine these various disciplines could lead to innovative and transformative solutions, ranging from 3D reconstruction and modeling of environments and landscapes to autonomous vehicle and drone navigation, as well as intelligent monitoring and maintenance of infrastructure and natural resources. These multidisciplinary integrations have the potential to revolutionize the way we perceive, analyze understand our physical world, opening new frontiers in applications such as urban planning, environmental management and disaster response.

## 5. Conclusions

This research has shown that the integration of deep learning techniques in photogrammetry has revolutionized the field, resulting in substantial improvements in the accuracy, efficiency and analytical capabilities of geospatial data. Innovative neural network architectures—such as Convolutional Neural Networks (CNNs), Generative Adversarial Networks (GANs) and Recurrent Neural Networks (RNNs)—have enabled significant advancements in image quality enhancement, change monitoring and semantic classification, allowing for a more comprehensive interpretation and understanding of data derived from aerial and satellite platforms.

The integration of deep learning techniques has significantly advanced the field of photogrammetry. By enhancing image quality through super-resolution and noise reduction methods, deep learning has enabled greater accuracy in 3D modeling and object detection. This has unlocked new possibilities for applications in areas such as precision agriculture, infrastructure management and environmental monitoring. Deep learning has significantly expanded the analytical capabilities of photogrammetry, enhancing our capacity to monitor and interpret geospatial phenomena with greater accuracy and detail.

While deep learning has brought substantial benefits to photogrammetry, several challenges must still be addressed. The need for large, high-quality training datasets and high computational costs pose notable barriers. Furthermore, the lack of interpretability in deep learning models and the need for more transparent architectures remain critical limitations that could hinder widespread adoption, particularly in applications where explain ability is essential. Nevertheless, ongoing research efforts aim to develop more efficient and accessible deep learning models, while improving the integration of various data sources and sensor modalities to further expand photogrammetric applications.

The future of deep learning in photogrammetry holds tremendous promise. As more sophisticated algorithms and advanced computational resources become increasingly accessible, we can expect a significant increase in the use and adoption of these techniques across a wide range of photogrammetric applications. Deep learning has the transformative potential to revolutionize the way we acquire, analyze and utilize geospatial data across many domains of geomatics and photogrammetry.

The use of deep learning in photogrammetry has not only enhanced the technical capabilities of the discipline but has also opened new and innovative opportunities for more efficient solutions and applications. As we continue to explore and develop these technologies, it is essential to address current challenges and work toward more accessible and transparent solutions that enable broader and more effective adoption of these groundbreaking techniques across various disciplines.

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